Using Temperature, Precipitation, and Solar Radiation Outputs from a Dynamically-Downscaled Global Climate Circulation Model to Predict Peanut Yields in the Southeastern USA

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ABSTRACT

Impacts of El Niño-Southern Oscillation (ENSO) phenomena on seasonal temperature and precipitation in Alabama, Florida, and Georgia have been well documented and can influence the yields of field crops grown in the region. The use of daily weather variables from historical ENSO climatologies to drive process-based crop simulation models provides a state-of-the-art means to forecast site-specific crop yields. However, the ENSO signal in the southeast is weak during the critical summer cropping period, June through September, thus ENSO climatology-based yield forecasts have more variability than is desirable and little forecast skill. Recent improvements in numerical climate models at both global and regional scales suggest an opportunity to enhance crop yield forecasts. Peanut crop yields were simulated using daily outputs from a regional spectral climate model (RSCM) embedded in the Florida State University global climate circulation model (GCCM) and were compared with yields simulated with observed historical weather conditions and those simulated with ENSO climatologies. Results indicate that temperature and solar radiation fields from the climate models contributed least to errors in peanut yield forecasts. Yield prediction errors from these two fields exhibited low temporal and spatial variability with little impact attributable to convection scheme. Yield prediction errors from precipitation fields were larger and were more temporally and spatially variable. Overall, the RSCM using relaxed Arakawa-Schubert convection had the lowest RMSE peanut yield across all years and sites. For temporal variability, the RSCM with simplified Arakawa-Schubert was comparable to ENSO climatology in some years and superior in 1994, 1997, and 1998. Effects of rainfall and temperature bias correction on the forecast error in peanut yields were small. Results suggest that application of RSCM forecasts may have the greatest immediate potential for simulating physiological processes that are most sensitive to temperature and relatively insensitive to rainfall, such as rates of crop development.

Keywords: *Arachis hypogaea*, climate forecast, crop simulation, dynamical downscaling, El Niño Southern-Oscillation

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INTRODUCTION

Impacts of the El Niño-Southern Oscillation (ENSO) on seasonal temperature and precipitation in Alabama, Florida, and Georgia, and in turn on various field crops have been well documented. In general, warm sea surface temperatures (SSTs) in the equatorial Pacific, the El Niño phase, defined here by the Japanese Meteorological Agency (JMA) index, are related to conditions that are anomalously cooler and wetter during the winter months. Conversely, cooler SSTs associated with La Niña conditions create anomalously warmer and dryer conditions in the spring. These shifts away from climatological norms can influence the yields of several field crops grown in the region (Jones et al., 2000; Hansen, 2002, Mavromatis et al., 2002). The use of daily weather variables from historical ENSO climatologies to drive a process-based crop simulation model, such as those found in the DSSAT 4.0 cropping system models, provides a state-of-the-art means to forecast site-specific crop yields (Jones et al., 2003).

The use of ENSO phase climatology is limited in several critical aspects. In practice, historical weather records have been categorized based on the JMA or other ENSO indices. Crop growth and yield simulations are made using each historical realization for the ENSO phase of interest and provides the yield expectation based on the conditions associated with that ENSO phase at a location. The use of historic climatologies prohibits the prediction of extreme events that exceed historical extremes. Extreme events are of particular interest in agriculture because most agricultural systems are well buffered against smaller variations around average conditions. The relatively short period of daily observations, approximately 50 years, also restricts the number of ENSO events for which robust data are available. Finally, the possibility of low frequency climate variability relative to the historic period of record may hinder the usefulness of data from early in the record to represent current conditions. Prospects for improvements in the skill of forecasts based on ENSO climatology is limited, because expected conditions associated with each phase change only marginally with the addition of new occurrences of the events.

Within the southeast, the ENSO signal is also weak during the critical summer cropping periods, June through September, when much of the determination of crop yield occurs. During this period ENSO climatology-based yield forecasts exhibit more variability than is desirable and limited forecast skill if the forecasts are to be used by producers for adaptive management. These problems provide the impetus to examine alternate approaches for linking information about climate variability with agricultural activities. While current weather forecasts have become increasingly accurate, the short period of accuracy (4 to 7 days in advance) makes them inappropriate for seasonal forecasts. Continuing improvements in numerical climate models at both the global and regional scales (Cocke and LaRow 2000; Kanamitsu et al. 2002; Palmer et al. 2004; Roads 2004, Shin et al., 2005) suggest that seasonal climate forecasts might produce crop forecasts that are more accurate than ENSO phase climatology alone and might improve the crop yield forecasts for this region during periods when ENSO phase alone provides limited information.

Process based crop simulation models are driven by daily weather variables; maximum and minimum temperature, precipitation, and incident solar radiation, to better reflect non-linear plant responses to variability in environmental conditions. The Florida State University global circulation model can simulate these variables with a daily time step, however, the large spatial resolution does not permit differentiation between yield potentials across the region. Several avenues exist for translating the forecast climate variables to smaller spatial domains. The use of statistical approaches such as those of Dubrovsky et al. (2000) and Phillips et al. (1998) have been effective in downscaling global model climate forecasts to smaller scales, though the approaches rely on the availability of high quality historical data and assume that the historical means for a location are not changing. This approach is also limited in responding to forecast events outside the range of historical data. Dynamically downscaling global climate forecasts by using a secondary climate model with better representation of land surfaces for the region of interest is an alternative approach (Juang and Kanamitsu 1994; Giorgi et al. 1994; Cocke 1998). The use of a smaller scale nested climate model, such as the FSU RSCM, may permit spatial and temporal resolution of climate variability at spatial scales that are of interest to producers when incorporated into yield forecasts.

While the potential value of seasonal climate forecasts to agricultural producers has been well established (Jones et al. 2000; Meinke and Stone 2005), the use of dynamically downscaled climate forecasts using regional climate models to drive crop simulations is not well studied. In this study we were particularly interested in the sensitivity of the crop yield forecast to the individual components of the climate forecast, e.g., temperature, precipitation, and radiation. Greater understanding of how the information generated by dynamically downscaled GCCM models can support crop yield forecasting will be useful in integrating climate and crop models and to support producer’s needs to manage production risks associated with climate variability.

METHODS

In this study, we used daily weather conditions for temperature, precipitation, and solar radiation to simulate growth and development of a warm season field crop. The predicted yields developed through the crop simulations were used to compare the quality of alternate sources of daily weather forecast data for predicting seasonal crop performance. The alternate sources of weather data are characterized below. We used climate model predictions of historical time periods to assess the quality of the forecasts by comparison against observed conditions. While climate model output might be better termed hindcasts, we refer to these simulation results as forecasts throughout this study.

Observed data

Observed conditions for the study were obtained from the records of the National Climate Data Center. For each of the nine locations, daily maximum and minimum temperature and precipitation were obtained from the TD3200 data sets (Cooperative Observer Network). Solar radiation data were estimated from daily temperature and precipitation using the approach of Hodges et al. (1985) based on normal distributions that have been parameterized separately for wet days and dry days at each site.

ENSO climatology

Climatology for El Niño, Neutral, and La Niña conditions were obtained from the TD3200 data. The JMA ENSO index was used to segregate the years 1948 - 2003 for each study location and the years identified for each phase were used to simulate crop performance. Crop simulation results for the years from each phase were averaged and provide the ENSO climatology yield forecast with the mean values taken as the best estimates of expected yield at a site for each phase of ENSO.

Climate forecast data

This study used the FSU regional spectral climate model (RSCM) nested within the FSU global climate circulation model (GCCM). The regional model produces climate outputs on a 20 km grid within the 200 km grids of the GCCM. The global and regional models are described fully in Cocke and LaRow (2000), Cocke (1998), and Shin et al. (2005). Atmospheric simulations were made for the periods of 1 Mar through 30 Sep for the years 1994 through 2003. Daily values for maximum and minimum temperatures, precipitation, and incident solar radiation (SRAD) were extracted from the gridded model output for the nine sites in this study based on the nearest grid point values from the RSCM data set. In this study, we used two separate methods for simulating convection; the Simplified Arakawa - Schubert (SAS; Pan and Wu 1994) scheme from the National Center for Environmental Prediction and the Relaxed Arakawa - Schubert (RAS; Rosmond 1992) scheme developed at the Naval Research Laboratory because in previous studies they provided better precipitation simulations than the RSCM/GCCM (Shin et al. 2006). Details of the RSCM and GCCM parameterizations used in this study are provided by Shin et al. (2006).

Bias-correction of RSCM output

The RSCM results are sensitive to the accuracy of the GCCM climate fields, which may exhibit bias that is carried to the RSCM during the nesting process. Thus, data from the RSCM simulations must be bias corrected prior to use as inputs to crop models. The bias correction applied here is described by Wood et al. (2002) and consists of remapping the cumulative probability distributions (percentiles) of the predicted data to those of the observed data. Bias was corrected individually for each site and for each calendar month of the forecast period using TD3200 historic observations. For example, if a RSCM value of maximum temperature lies at the 60th percentile of the RSCM maximum temperature distribution for a location, the bias-corrected value would be the 60th percentile of the maximum temperature distribution in the observation data. This effectively removes any systematic error in RSCM output values. This step is particularly important for precipitation, because the RSCM tends to produce a large number of wet days with small precipitation amounts. In this case, bias correction reduces the number of wet days by remapping trace precipitation to zero.

Synthetic data sets

We developed synthetic weather time series for the purpose of examining the forecast of individual climate fields on crop simulations and the resultant yield forecasts. Time series were developed from forecasts using both convection schemes. For temperature, precipitation, and solar radiation, climate forecast values were systematically substituted with observed conditions, e.g., observed maximum and minimum temperature, observed SRAD, plus predicted precipitation 1994-2003. With this technique, maximum and minimum temperatures were substituted simultaneously. The synthetic weather data allowed us to examine the impact of forecast temperature, precipitation, and solar radiation produced by the FSU RSCM using each convection scheme. This approach does not completely account for daily correlations between climate fields but rather provides an appropriate temporal autocorrelation for each variable in turn and evaluates the RSCM outputs with the assumption of perfect prognosis for the remaining individual fields.

Crop simulation model

The CropGro peanut cropping system model was used and run within the Decision Support System for Agrotechnology Transfer Environment (DSSAT v 4.0; Jones et al. 2003). CropGro is a dynamic, process-based model that simulates how crop development, crop carbon balance, soil-crop-atmosphere water balance, and crop and soil nitrogen balances respond to different weather conditions, soil profiles, and management. The model uses sub-modules for plant, soil, and environmental processes and soils, management-, and species-specific genetic parameters from pre-prepared files. The model uses maximum and minimum temperature, precipitation, and solar radiation (SRAD) from daily weather time series. It computes plant physiological development, growth, and partitioning processes daily for a specific site, from planting to maturity. As a result, impact of weather variables, soils, and management decisions on the crop yield can be well estimated.

Simulation design

The CropGro model was parameterized for ‘Georgia Green’ peanut and simulations were made for the period 1994 through 2003 (Table 1) at nine sites across AL, FL, and GA (Figure 1). Management options consisted of a 25 Apr planting date, no fertilization, no irrigation, and local soil profiles based on US Soil Conservation Service county data for each site. Simulations were initiated prior to the simulated planting dates to permit soil water balances to equilibrate with the relevant climate data before crop initialization. Peanut development and yields were simulated using alternate sources of daily weather data to drive the model. Data sources consisted of the historically observed conditions at each site, climatology for each ENSO phase (1948-2003), the raw RSCM output using the SAS and RAS convection schemes, bias-corrected RSCM output for SAS and RAS, and synthetic datasets produced by combining observed conditions with forecast variables from bias-corrected RSCM SAS / RAS for each climate variable. Simulations for each combination of site, year, and weather data source were allowed to progress to physiological maturity. In field and post-harvest losses were not considered.

Table1. Crop simulation sites and soil profiles for ‘Georgia Green’ peanut, 1994-2003, using observed, climate model, and synthetic weather data.

Site name	Site code	County	Soil	Lat. (N)	Long. (W)
Andalusia, AL	AL02	Covington	Dothan Loamy Sand	31.30	86.52
Bay Minette, AL	AL06	Baldwin	Orangeburg Sandy Loam	30.88	87.78
Clayton, AL	AL15	Barbour	Dothan Loamy Sand	31.88	85.48
Alachua, FL	FL33	Alachua	Millhopper Sand	29.70	82.28
Quincy, FL	FL71	Gadsden	Orangeburg Sandy Loam	30.60	84.55
Chipley, FL	FL11	Washington	Orangeburg Sandy Loam	30.78	85.48
Camilla, GA	GA11	Mitchell	Tifton Loamy Sand	31.18	84.20
Tifton, GA	GA57	Tift	Tifton Loamy Sand	31.45	83.48
Vidalia, GA	GA35	Toombs	Tifton Loamy Sand	31.93	81.93

Analysis

Whereas previous evaluations of RSCM output have primarily examined monthly moments (Shin et al, 2006), in this study we evaluated the ability of FSU RSCM output relative to its ability to serve as daily input to crop model simulations. Monthly moments are too coarse to provide guidance relative to crop simulation models that operate on a daily time step. On the other hand, evaluation of daily performance is not warranted because of short-term memory within the crop system. Thus, a series of five-day periods were used to assess the quality of the forecasts relative to observations and was considered reasonable given the non-linear response of crop simulations to daily conditions. Running means were calculated for each climate variable using both raw and bias-corrected RSCM SAS and RAS output.

We compared simulated crop yields using observed weather with simulated crop yields using RSCM forecasts by ANOVA and root mean squared error (RMSE). Spatial variability in yield prediction errors was examined by considering the RMSE for all ten years at each study site. Likewise, temporal variability in yield forecast errors was examined using the RMSE during each year across the 9 study locations.

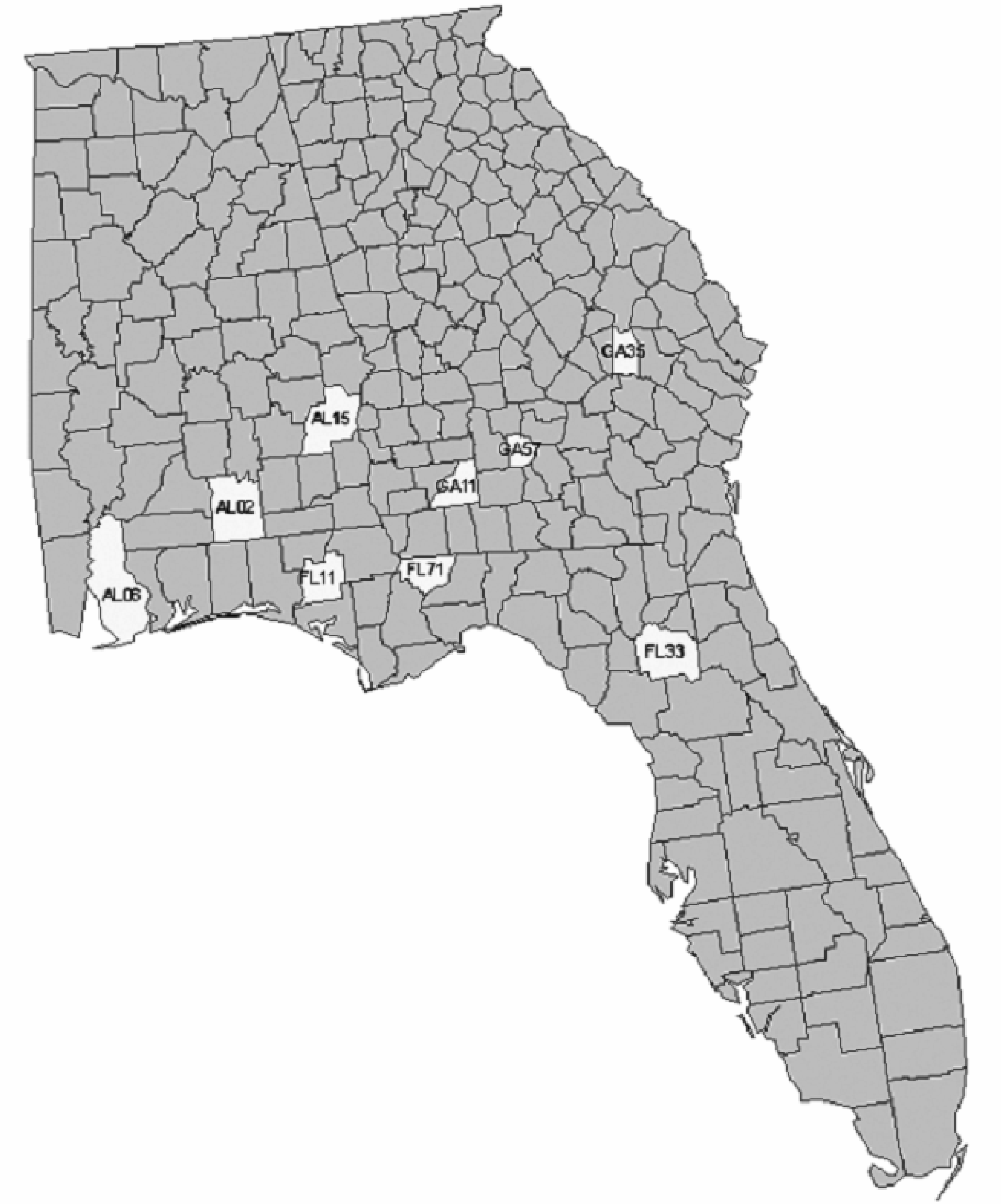


Figure 1. Map of study locations for assessment of FSU RSCM forecasts 1994-2003 using DSSAT 4.0 CropGro for peanut.

RESULTS AND DISCUSSION

Bias-correction

Comparisons of SAS and RAS forecasts among sites for each climate field are shown in Figure 2. The RMSE of maximum temperature was less for bias-corrected RAS output (2.8 ± 0.25 °C) than for bias-corrected SAS (3.0 ± 0.25 °C). For minimum temperatures, RMSE for bias-corrected RAS (3.2±0.29 °C) was not significantly different from that for SAS (3.3 ± 0.28 °C). Similarly, for precipitation RMSE of bias-corrected RAS (9.3 ± 2.7 mm) was not significantly different from and that of bias-corrected SAS (9.4 ± 2.4 mm). While SRAD values were not corrected for bias, 5-day mean SRAD from the RSCM RAS forecast (4.0 ± 0.39 MJ d^{-1}) compared more favorably with observations than did that for SAS (4.5 ± 0.27 MJ d^{-1}). For both maximum and minimum temperatures, a small amount of error at each site could be removed through bias correction (Figure 2). However bias correction of daily precipitation was not effective. In general, using observed probability distributions to correct forecast distributions increased rather than decreased the error in mean 5-day precipitation. Increase in total error was greater in Alabama than in Georgia locations. Additionally, bias correction introduced more error into the RSCM SAS forecast scheme than the RAS scheme. The failure of bias correction to substantially improve precipitation forecasts was in contrast to our expectations and suggests the need for additional assessment of bias correction for precipitation.

Spatial variability

The bias corrected forecast using RAS was slightly less variable across the region than that using SAS, though differences were not significant (Figure 3). Over the region, mean error in dry seed yield for 1994-2003 was 1727 kg ha^{-1} when simulated using RAS compared with 1858 kg ha^{-1} when simulated using SAS. Using synthetic forecasts, we were able to examine the spatial variability in yield prediction errors that could be attributed to errors in temperature, precipitation, and solar radiation forecasts. The contribution of forecast temperatures to total forecast error was 12% for forecasts made using the RAS convection scheme and 14% SAS (Figure 3). Spatial variability in yield forecasts due to temperature predictions was small with errors ranging from 130 to 272 kg ha^{-1} for RAS and 155 to 360 kg ha^{-1} for SAS.

Yield prediction errors that could be attributed to the use of precipitation forecasts were much greater than those for temperature. Simulations using forecasts with the RAS or SAS convection schemes had similar errors of 86% and 88%, respectively. Errors related to forecasts of rainfall were highly variable across the study region and ranged from 832 to 2952 kg ha^{-1} for RAS and from 866 to 2765 kg ha^{-1} for SAS. There are some indications that the RAS and SAS precipitation forecasts predict seed yield better at inland sites compared with those nearer the coast (Figure 4).

Errors in predicted yields that can be attributed to SRAD were 11% for RAS and 10% for SAS. Spatial variation in errors due to predicted SRAD was small, from 92 to 407 kg ha^{-1} for RAS and between 90 and 229 kg ha^{-1} using SAS (Figure 5).

Yield predictions using bias corrected RAS and SAS forecasts were compared with yield predictions using historic weather observations. Mean yield predictions for JMA ENSO phases based on historic climatology were assigned for each year of the study and compared to yields simulated using that year's observed weather. The RMSE of peanut dry seed yields predicted by ENSO phase climatologies at each location ranged from 940 to 1965 kg ha during 1994 through 2003. This error was significantly less than the error produced using the SAS forecast (paired t-test, $p = 0.008$), though it was not significantly different from errors produced using RAS (Figure 6).

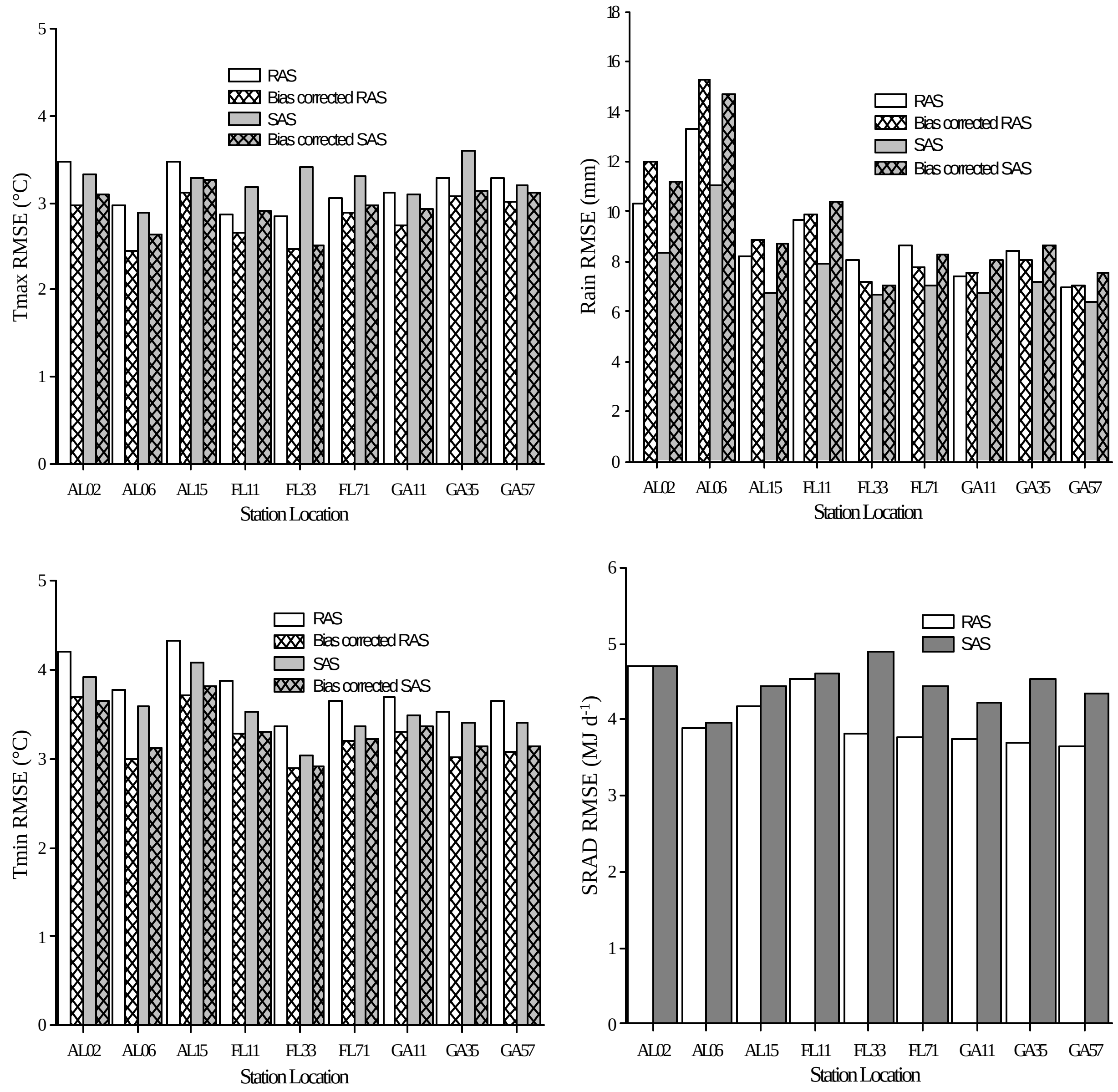


Figure 2. Dynamically downscaled GCCM fields (Tmax, Tmin, Rain, and SRAD) compared to observations at nine Southeastern locations during 1 Mar - 30 Sep (1994 - 2003). For each climate variable, forecasts and the observations were compared using 5-day running means.

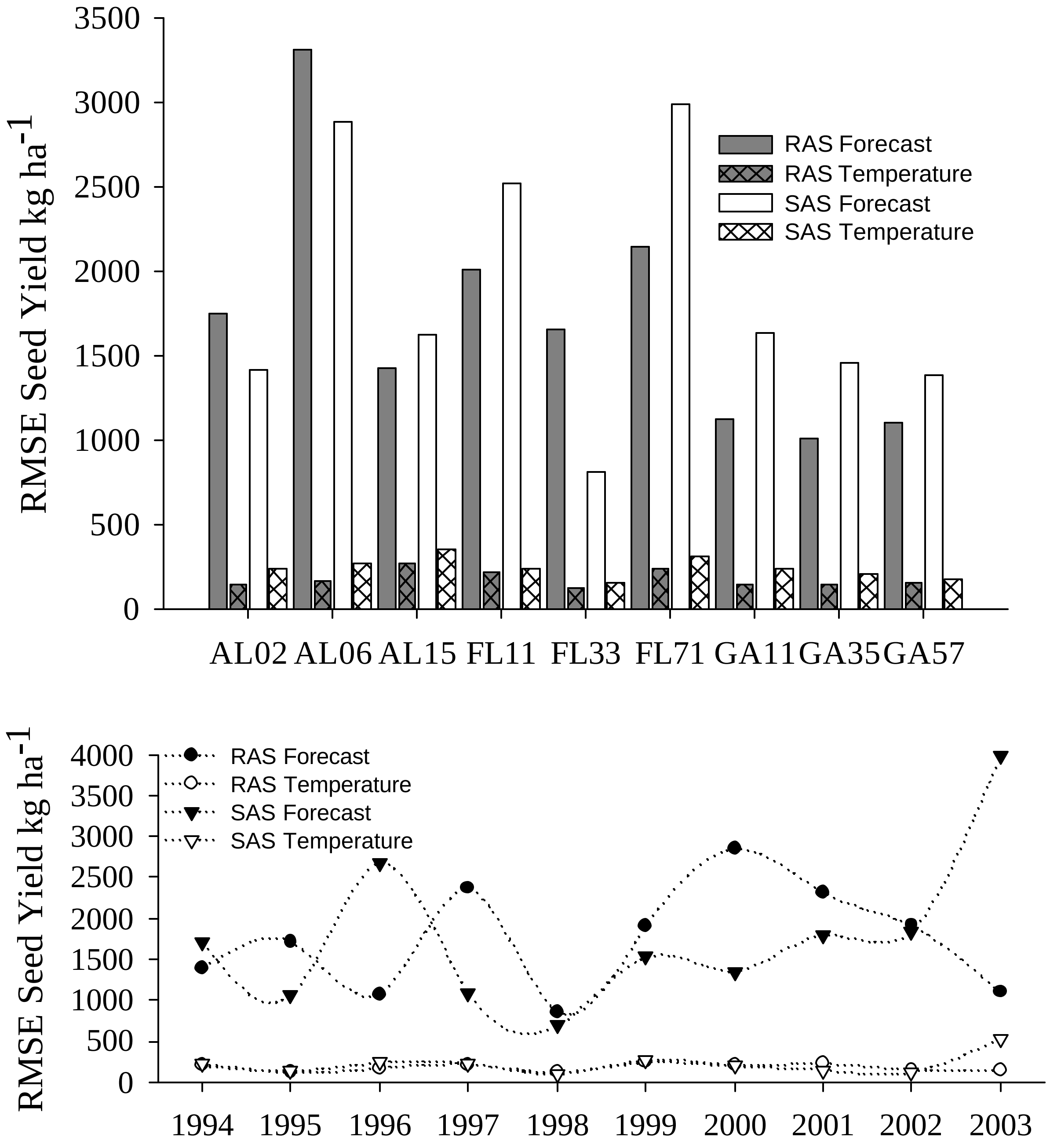


Figure 3. Spatial (top) and temporal (bottom) variability of errors in ‘Georgia Green’ peanut dry seed yield forecasts based on FSU RSCM forecasts and on temperature field forecasts only for nine southeastern US sites during 1994 - 2003.

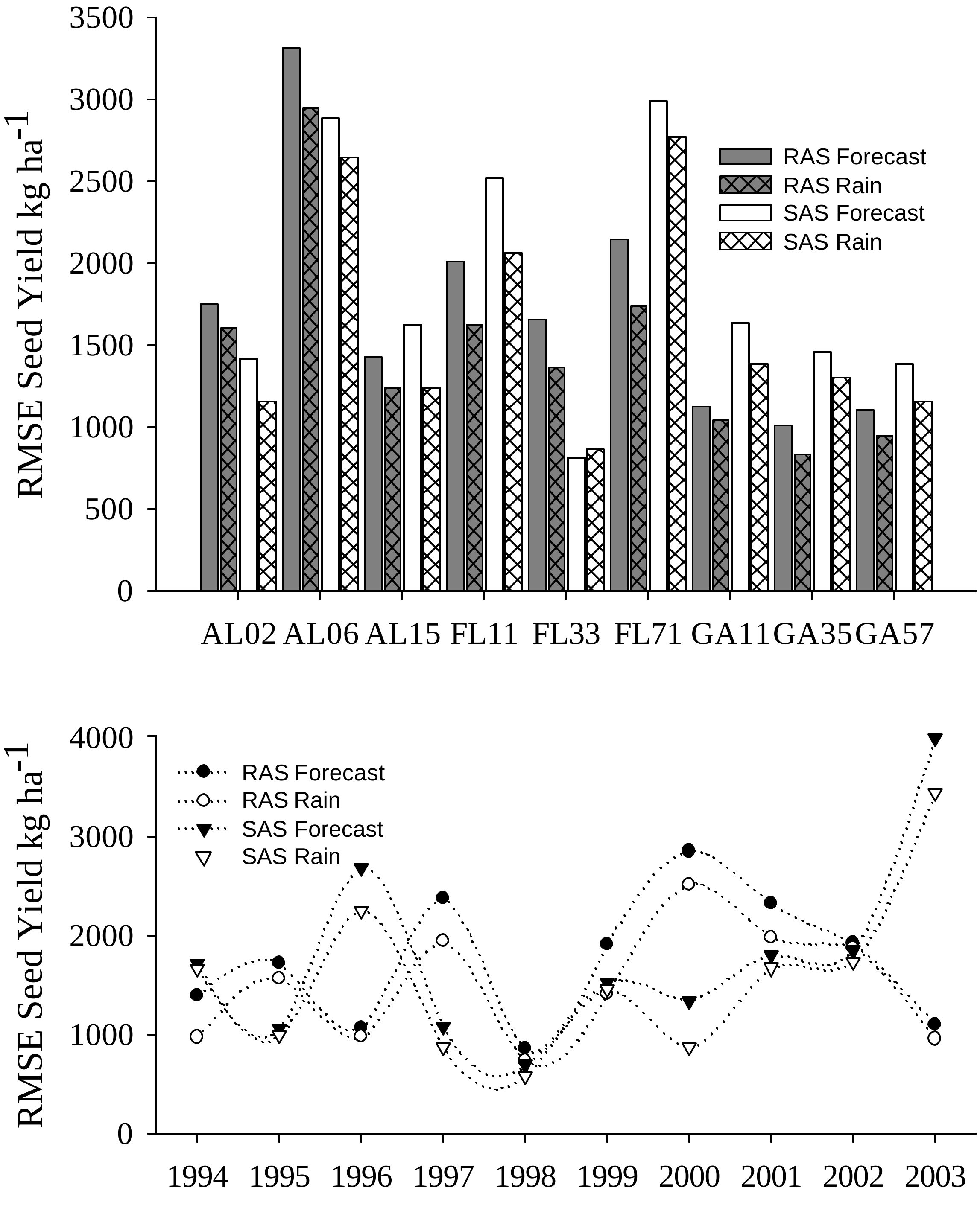


Figure 4. Spatial (top) and temporal (bottom) variability of errors in 'Georgia Green' peanut dry seed yield forecasts based on FSU RSCM forecasts and on precipitation forecast fields only for nine southeastern US sites during 1994 - 2003.

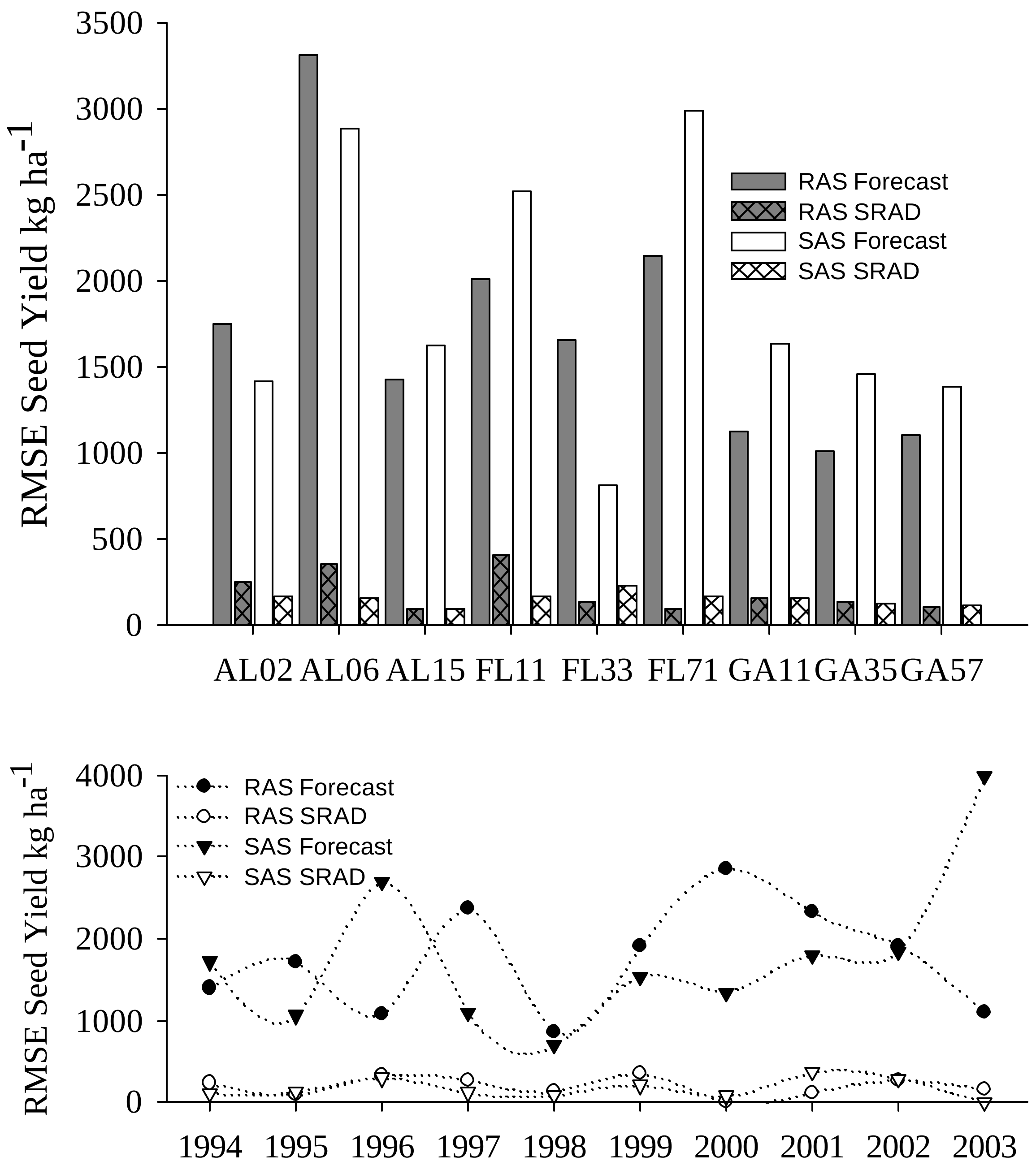
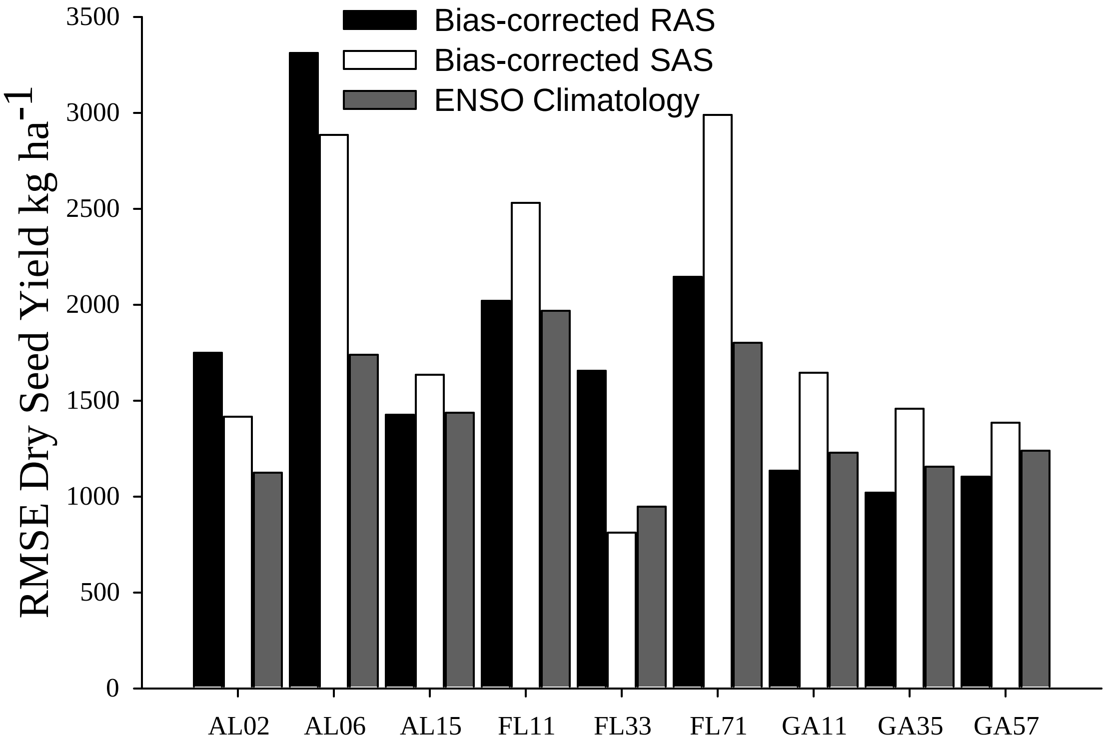


Figure 5. Spatial (top) and temporal (bottom) variability of errors in ‘Georgia Green’ peanut dry seed yield forecasts based on FSU RSCM forecasts and on solar radiation forecast fields only for nine southeastern US sites during 1994 - 2003.



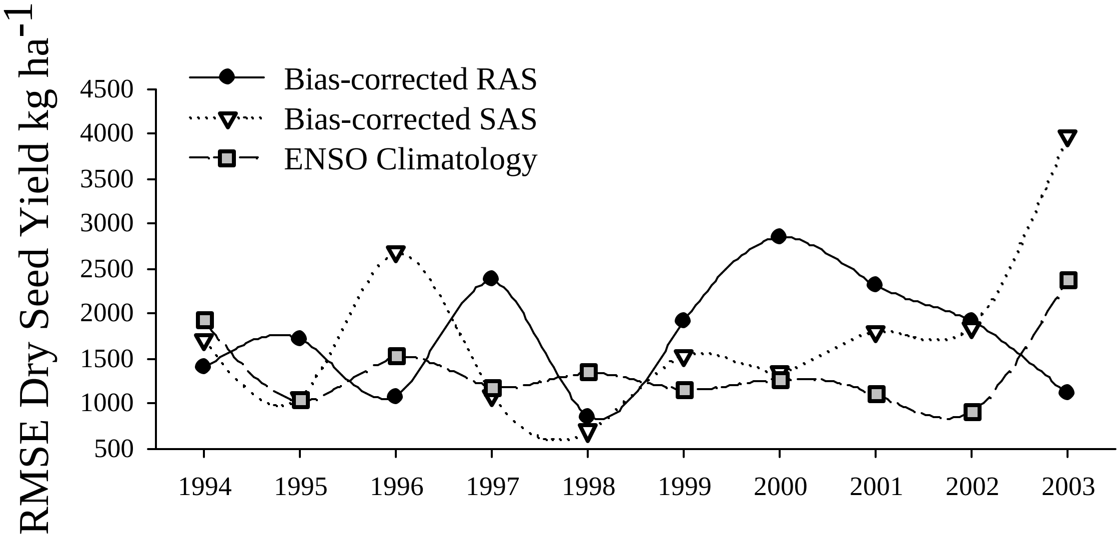


Figure 6. Comparison of spatial (top) and temporal (bottom) errors in simulated peanut dry seed yields based on RSCM climate fields using RAS and SAS convection parameters, and forecasts based on ENSO climatology.

Temporal variability

Temporal variability in yield prediction errors (RMSE) is much greater from among years than what was observed between locations. Using the bias-corrected RAS forecasts RMSE in predicted yield ranged from 854 to 2847 kg ha^{-1}; using the bias-corrected SAS forecasts RMSE ranged from 695 to 3984 kg ha^{-1}. There was no significant difference between the RMSE produced using the two forecast sources. Magnitude of yield prediction errors using the two forecasts also appear unrelated to the JMA ENSO phase. While the smallest errors in predicted yield occurred during 1998, a strong La Niña year as defined by the JMA ENSO index, actual conditions in the equatorial Pacific were neutral during the simulation time period. Additionally, there was no evident pattern related to other ENSO events during the study period (Figure 6).

After bias-correction, forecast temperature values contributed to a small fraction of the total RMSE of predicted yield during each year. Temperature from RAS accounted for 11% of the RMSE in predicted yield compared with 13% when the SAS forecast was used (Figure 3). Similarly, error in yield predictions due to differences in SRAD forecast were relatively low, with 14% of the error when using the RAS forecast and 12% associated with the forecast produced with the SAS model (Figure 5). After bias correction differences in frequency and quantity of precipitation forecast by the two models was the largest source of error in yield forecasting using both convection schemes. The RMSE attributable to precipitation using SAS forecasts was 87% while the error when using the RAS forecast was 85% (Figure 4). The range of RMSE across the 9 sites ranged from 854 kg ha^{-1} in 1998 to 2847 kg ha^{-1} in 2000 for the RAS scheme, whereas those for the SAS model ranged from 695 kg ha^{-1} in 1998 to 3984 kg ha^{-1} in 2003. The 'state-of-the-art' approach using ENSO climatologies had a range of 901 kg ha^{-1} in 2002 to 2370 kg ha^{-1} in 2003. During the 10-year period studied, the RAS forecast scheme was as good as or better than ENSO-based methods 40% of the time, and the SAS forecasts scheme was as good as or better than ENSO based methods 50% of the time.

The low contribution of model forecast temperature fields to RMSE indicates that these fields may contain quality information relative to plant development. Errors in the yield forecast due to precipitation and SRAD were removed by substitution with observed values and the resultant yield forecast was significantly better at all study sites and during all years (Figure 7). Here, the RAS temperature forecast was consistently superior to the SAS forecast at individual locations during 1994-2003. Although crop yields result from complex interactions among multiple climatic factors, plant genotype, soil characteristics, and crop management practices, these results strongly suggest that additional agricultural applications that are more dependent on temperature fields be considered as avenues to exploit fully the value of dynamically downscaled regional climate forecasts.

CONCLUSIONS

This paper examined the use of outputs from two seasonal climate forecasts from a dynamically downscaled numerical climate circulation model to forecast peanut yields in the Southeast United States. The two models differed in approach to parameterize convection. The individual climate fields used as inputs to a peanut crop growth and development simulation model were systematically examined through the use of synthetic forecasts. Yield forecasts based on downscaled climate models were also compared with yield forecasts that could be produced using ENSO climatology based on the JMA index.

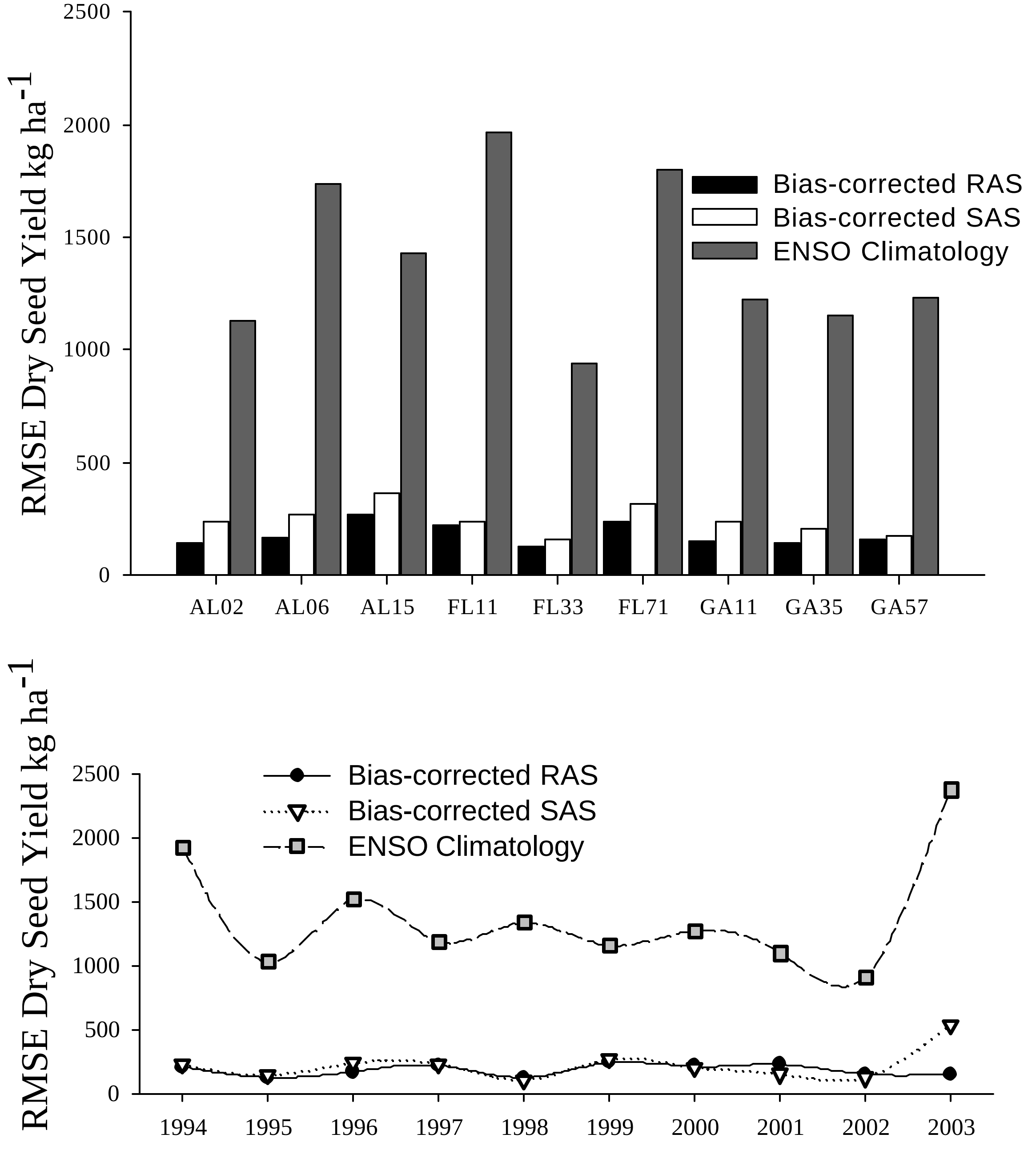


Figure 7. Spatial (top) and temporal (bottom) errors for best-case forecasts using FSU RSCM (perfect prognosis of precipitation and SRAD with forecast temperatures) compared with errors for forecasts based in ENSO climatology at each site.

Neither method for parameterization of convection within the FSU RSCM produced consistently superior forecasts compared with ENSO climatology for the purpose of seasonal forecasting of peanut yields in the Southeast. While RSCM performance was positive following strong ENSO events (1994, 1998), there is currently insufficient data to generalize this observation and further study is warranted. This limitation should be addressed by the extension of the available forecast years to include additional ENSO events.

Bias correction of daily maximum and minimum temperatures reduced errors associated with forecasts using both RAS and SAS models when assessing the 5-day average for each of these fields. On the other hand, bias correction of precipitation did not consistently reduce errors in forecasts when averaged over 5-day periods. Bias correction based on mapping the forecast probability distributions onto the historical distribution at each site was not an acceptable method for enhancing the forecasts for the purposes of predicting crop yields during the 10-year historical period examined. These results indicate that alternate approaches to bias correction of model forecasts must be considered if systematic errors are to be addressed.

The climate fields considered individually in this study did not contribute equally to the errors in simulated peanut yields. Temperature fields (daily maximum and minimum) produced relatively small errors in simulated peanut yields. Spatial and temporal variabilities in the contributions of temperature fields to error were also small. Errors in forecast incident solar radiation also produced small errors in simulated yields with low variation between sites and between years. Errors associated with the precipitation field, however, produced large errors in simulated yield predictions. Total error in yield prediction was more variable from site to site and among years than errors attributed to forecasts of temperature or solar radiation fields; nonetheless the fraction of the forecast error attributable to precipitation was surprisingly constant. The approach we used substituted observed conditions within each climate field for the forecast conditions. The resultant reduction in correlation between climate fields on a daily basis is thought to have introduced additional error into yield predictions that could not be assigned to individual climate variables.

Peanut crops are known to be sensitive to both temperature and precipitation during much of the growing season, making them a suitable crop for evaluating the forecasts. Still, the use of a single crop species may limit our ability to draw broader conclusions about the utility of the forecasts. Further work should include comparisons using alternate crop types such as the *Graminae* or consider determinate crops with a shorter period of sensitivity and yield response to precipitation deficits. The adequate performance of the temperature fields for peanut simulation model suggests that further examination of these fields for crop performance is needed apart from precipitation effects.

As the primary influence of temperature is on rates of crop development, models that simulate crop phenology or that predict growing degree days may make better use of information embedded within downscaled climate forecasts. Availability of phenological predictions may support improved decision making relative to crop management and marketing. Future work needs to examine the performance of phenological models driven using seasonal temperature forecasts and characterize the conditions where downscaled climate model forecasts outperform ENSO climatologies. Particularly where producers have access to irrigation, forecasts of thermal unit accumulations made with the FSU RSCM may be useful in managing production risks.

Use of outputs from dynamical downscaled climate models did not provide substantial advantage in forecasting peanut yields over those methods that used ENSO climatology. Though errors in temperature and solar radiation fields were small, additional improvements in precipitation forecasts are needed to improve the resultant yield forecasts using crop simulation models. Generation of multiple forecasts differing in initial conditions may both allow tests of sensitivity to initial conditions and allow selection of a superior subset of forecasts to be used in predicting seasonal crop performance. This approach will be studied in subsequent work using the FSU RSCM. Finally, the role of feedback between climate and crop models should be considered and a coupled version of atmospheric and crop models should be developed to capture nonlinear seasonal weather-yield interactions.

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