6.9 THE LINKAGE OF REGIONAL CLIMATE MODELS TO CROP MODELS

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1. INTRODUCTION

Agriculture is Florida's most weather-sensitive sector. There is a well-documented interest by growers and ranchers in Florida for advance information on the climate of the upcoming agricultural season. Seasonal forecasts offer the potential to modify outcomes and risks, and hence, impact decisions.

Crop models are frequently used to evaluate the ability of climate forecasts in guiding crop management practices. There are three main approaches for creating climate scenarios appropriate for driving site-based crop simulation models. The first approach involves using site historical data, sometimes categorized into classes statistically (i.e. precipitation terciles) or using ENSO phases (i.e. Phillips et al., 1998; Jones et al., 2000; Mavromatis et al., 2001). The second approach involves training a weather generator with observed data and global climate model anomalies to create perturbations (Rajagopalan and Lall, 1999; Wilks, 1999). Finally, output from a global or regional climate model can be used as direct input into a crop model (Mearns et al., 1999). Until now, agricultural applications of climate forecasts have used statistical analysis of historical climate and ENSO information to arrive at climate scenarios for adaptive management (Jagtap et al., 2001a; Mavromatis et al., 2001; Jones et al., 2000; Ferreyra et al., 2000; Podesta et al., 1999; Messina et al., 1999; Phillips et al., 1998; Meinke et al., 1996).

Weather generators have found limited use in previous studies due to several inherent limitations. These methods cannot be used for locations for which there are no historical data (Dubrovsky et al., 2000) or if the length of the historical data series is not long enough. The interaction of climate change with climate variability, ultimately, will limit utility of weather generator or historical analogue based approaches. Another limitation of using generated data lies in the fact that although the means of crop yields may be produced, the variances and frequencies of extreme events are not always captured by the generated data (Mearns et al., 1996, 1997).

Optimization studies in the southeast United States (Jones et al., 2000) show overwhelmingly that eleven to fifteen times more profit can be derived using perfect forecasts of the next season's daily weather compared to a precipitation-based categorical forecast and forecast conditioned on ENSO phase, respectively. However, the availability and accuracy of the next seasons daily weather forecasts is a major challenge. The skill levels of global and regional climate models, which are used to generate these forecasts, have been shown to be less accurate than statistical methods. Although the tools and ability to model and predict seasonal climates have been improving over the years, previous models have shown deficiencies in many aspects. These deficiencies include: a lack of spatial and temporal accuracy, poor reliability of global simulated atmospheric circulation patterns, low magnitude of correlation between the circulation and surface weather, and a lack of reliability of surface weather simulated by the regional model. These models often have coarse resolution and do not take into account important local conditions, such as coastal or mountainous features. All of these factors can affect the use to which climate information can be put and the level of generalization that can be assumed and subsequently, the response of users and their continued trust in such information (Jagtap et al., 2001a). Nevertheless, these global and regional models take into consideration large-scale phenomena and integrate them with local topographic and land use characteristics, and thus are expected to provide somewhat accurate site- and year-specific climate forecasts.

Future improvements in climate prediction science and forecast products are expected to come largely through larger ensemble datasets and improved dynamic climate models whose output can be used directly for agricultural applications (Phillips et al., 1998; Cane 2001; Druyan et al., 2001;Goddard et al., 2001). Therefore, even though their skill levels are still being investigated, it may be beneficial to couple agricultural models with the regional climate models for producing relevant information for use by agricultural decision makers.

The appropriate methodology for linking climate prediction and crop simulation models has been identified as a critical knowledge gap. The goal of this work was to examine these issues through a case study involving the integration of the Florida State University regional nested climate model (Cocke and LaRow, 2000) with a maize model in the widely used DSSAT family of crop models. The growing seasons during 1998 and 1999 were chosen because they represent significantly different climate regimes: 1998 was an El Niño year and 1999 was a La Niña year. Descriptions of the climate models and crop models will be summarized in Sections 2 and 3. Preliminary results from this study will be discussed in Section 4.

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2. NESTED REGIONAL SPECTRAL MODEL

The climate model used in this study is a regional spectral model embedded within a global coupled ocean-atmosphere spectral model. The regional model is a re-locatable spectral perturbation model that can be run at any horizontal resolution and uses base fields and sea surface temperatures derived from the coupled global model as boundary conditions. The vertical structure of the global model consists of 14 unevenly spaced vertical levels and it is coupled to the Max Planck global ocean model (HOPE). Details of these models and the model physics are available in Cocke and LaRow (2000).

Two six-month experiments were conducted for the growing seasons (March-August) of 1998 and 1999. A ten-member ensemble was constructed for each year to assess uncertainty in initial conditions and variability of forecasts in space and time. Each ensemble member was six months (184 d) long with atmospheric initial conditions chosen from consecutive start dates centered on 1 March, obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). The coupled model was initialized with a spun-up ocean state [see Cocke and LaRow (2000) for more details]. The global model was run on a coarse grid spacing of ~200 km and the regional model on a fine scale resolution of ~20 km.

Weather data in a grid cell containing Quincy, Florida (30.6°N, 84.55°W) were extracted from both model sets of ensembles for statistical analysis and crop model runs. Observed daily maximum and minimum temperatures and precipitation data were also collected for Quincy from the Florida Climate Center from 1968-1999. Missing daily radiation data at Quincy were replaced by daily radiation data from Tallahassee, Florida, located 50km to the southeast. Results from the regional and global models were compared to the observed weather at Quincy in 1998 and 1999 to evaluate how well these models reproduced the observed weather. The regional model results were also compared with those from the driving global model to assess the extent to which the nesting modified, and possibly improved, the resulting forecasts. Temperature (maximum and minimum), radiation, and total rainfall averaged for the March-August months for ten ensembles of the global and regional models were compared with observed weather data.

3. CROP MODEL

The CERES-Maize simulation model (Ritchie et al., 1998) was used to delineate effects of various forecasts on simulated maize yield. The CERES-Maize model is a dynamic process based crop model that simulates how corn plants respond to soil, weather, water stress, and management. Using site-specific input data, it calculates development, growth, and partitioning processes on a daily basis, starting at planting and ending when harvest maturity is predicted. As a result, the response of the corn plant to different soils, weather, and management conditions can be predicted. The model is well suited to addressing the impacts of weather/climate variability (Mavromatis and Jones, 1998; Mearns et al., 1999), and on the choice of management decisions (Jones et al., 2000; Hansen et al., 2001).

4. DISCUSSION

4.1 *Global and Regional Model weather in 1998 and 1999*

Temperatures forecast by the global and regional models for Quincy were similar in 1998, but rainfall was considerably different (Figure 1). The regional model rainfall forecast in 1998 was comparable to both categorical ENSO and local climatology, but it was over-predicted at Quincy by a total of 300 mm for the period April-June and under-predicted by about 160 mm for the period July-August. Thus, in 1998, the bias between observed rainfall and forecast rainfall were of the same order of the observed categorical or climatological values. Not surprisingly, there were highly significant differences between observed and predicted monthly values with the regional and global models in 1998. The regional model showed higher skill in predicting rainfall at Quincy in 1999 (Figure 2).

Early season maximum temperatures were colder than observations, local climatology, and the average El Niño year for the early part of the season (Figure 1) but slightly warmer than observed in July and August of 1998. Minimum temperatures also exhibit a slight cold bias in both the global and regional models in 1998 (Figure 1). This cold bias is higher in the global model simulations than the regional model. This bias was also noted by Cocke and LaRow (2000) in their study of boreal winters in North America. They suggest that these biases (on the order of 3^oC) may be reduced with the inclusion of a better land surface parameterization scheme. Temperatures in 1999 (Figure 2) are observed to have similar biases as noted in 1998, although the magnitude of the bias is less, on average, for both models. Monthly average solar radiation values at Quincy in both 1998 and 1999 seasons were over-predicted by 8-10 MJ m^{-2} d^{-1} from June-August (Figs. 1, 2), which coincides with the grain filling period and was about 38-50% higher than the seasonal average radiation of 21 MJ m^{-2} d^{-1}.

Due to the chaotic behavior of the atmospheric circulation patterns, forecasts based on climate models may have considerable uncertainty. The global model generally produced less precipitation than the regional model in all months in both 1998 and 1999. The difference between the regional and global rainfall amounts at Quincy was especially large over the forecast period (+260% in 1998 and +360% in 1999). These differences may be related to how rainfall events are simulated by each of these two models and by their proximity to coastal areas. Note that the case study region is not characterized by significant local topographic variability, so these differences are not likely due to the local topographical forcing. This result shows that, even with the same large scale driving fields, a global model and nested regional model can show distinctly different spatial rainfall pattern on the sub-regional scale, particularly during the crop-growing season.

4.2 *Crop Results*

In 1998, none of the forecasts (measured by either mean or most likely yield) predicted the 1998 yield of 7.2 Mg ha^{-1} correctly (Figure 3, Table 1). The yield simulated using 1998 weather was significantly lower (Table 1, p=0.05) than yields produced by all forecasts. The differences in maize yield forecasts arise because of the non-linearity of crop responses to weather. Expected yields from 30-yrs of historic weather data ranged from 6.12 to 11.89 Mg ha^{-1} with a mean of 9.90 Mg ha^{-1} and standard error (*s.e.*) of 0.25 Mg ha^{-1}. The range of yields estimated in El Niño years was smaller and ranged from 9.10 to 11.84 with a mean of 10.31 and *s.e*. of 0.37 Mg ha^{-1}. The 1998 yield of 7.2 Mg ha^{-1} was outside the range of yields expected using El Niño forecasts. Climatologically and using regional model forecasts, the probability of such a low yield was about once every 10 years or 10%. Prediction error (PE) (measured as the difference between the expected yield using a forecast and yield in 1998 using the same forecast specific management) varied from a low of +2.7 Mg ha^{-1} using climatological forecast to a high of +3.80 Mg ha^{-1} using regional model based forecasts (Table 1).

Weather patterns during 1998 were unique. Worldwide, 1998 was rated as the strongest El Niño event of the century. Although El Niño events typically bring plentiful winter rains to North Florida, the early summer months (May and June) are often quite dry following a warm event; 1998 was no exception. These extreme dry conditions combined with 2-5°C higher than normal maximum and minimum temperatures during the most water sensitive stages of corn growth reduced yield considerably. From yield distributions in Figure 3, it can be seen that the simulated 1998 yield was one of the lowest (probability <10%). In 1998, the average statewide corn yield was 3.9 Mg ha^{-1} or 23% less than 1997 or 1999 yields. Statewide yield was considerably lower than our simulation because we did not account for the reality of inadequate use of fertilization, untimely management practices, weeds, and insect pests. Although the CERES-Maize or similar models enable us to represent and predict the interactive effects of climate, soil, varieties and management, we will never be able to understand and predict all mechanisms. The results reported here are to be taken as general indicators rather than precise values.

The 1999 cropping season was a La Niña year with normal rainfall and resulted in a simulated yield considerably higher (13.94 Mg ha^{-1}) than yields predicted using 30-yrs of climatological or 6-yrs of La Niña based forecasts (Table 1). The regional model-based forecast accurately predicted the observed 1999 yield (Figure 3). Predictions based on climatology, ENSO and rainfall categories in 1998 and 1999 exhibited little skill, while the regional model forecast the 1999 yields with more accuracy.

5. CONCLUSIONS

We face many challenges as we seek to enhance the exciting prospect of bringing scientific seasonal climate forecasts to bear on agricultural systems. A skillful seasonal weather forecast provides an opportunity for growers to better tailor crop management decisions before the season. However, the highest benefit and success rate generally comes from the spatio-temporal accuracy of the weather forecast itself. Presently, there is a capability to forecast synoptic weather (daily rainfall, temperatures and global solar radiation) specific to location/region by regional models nested within global models driven by the present state of the oceans. In their present form, most forecast products lack the spatial, temporal and element of specificity that users seek for specific decision making needs, however, with time this problem will be overcome. This development is of particular importance for the application of seasonal climate forecasting in targeting and presenting the information within a time frame consistent with operational requirements and at a spatial scale appropriate to users' needs.

Results from this preliminary study indicate that the regional climate model exhibits some skill in the prediction of crop yields. More work needs to be done to evaluate the skill of the model and to determine if the model has similar skill during other seasons, different locations, or different crop types. Improvements to the model physics are currently underway and the newer version of the model will be tested in the near future. More details of these results are available in Jagtap et al. (2001b).

6. ACKNOWLEDGEMENTS

The Center for Ocean–Atmospheric Predictions studies (COAPS) receives its base funding support from the Secretary of the Navy Grant to James J. O'Brien. This work was supported by NOAA Grants NA76GP0521 and NA86GP0031. This work represents a cooperative effort between COAPS and the University of Florida. All climate models are run at COAPS and crop models are run at the University of Florida.

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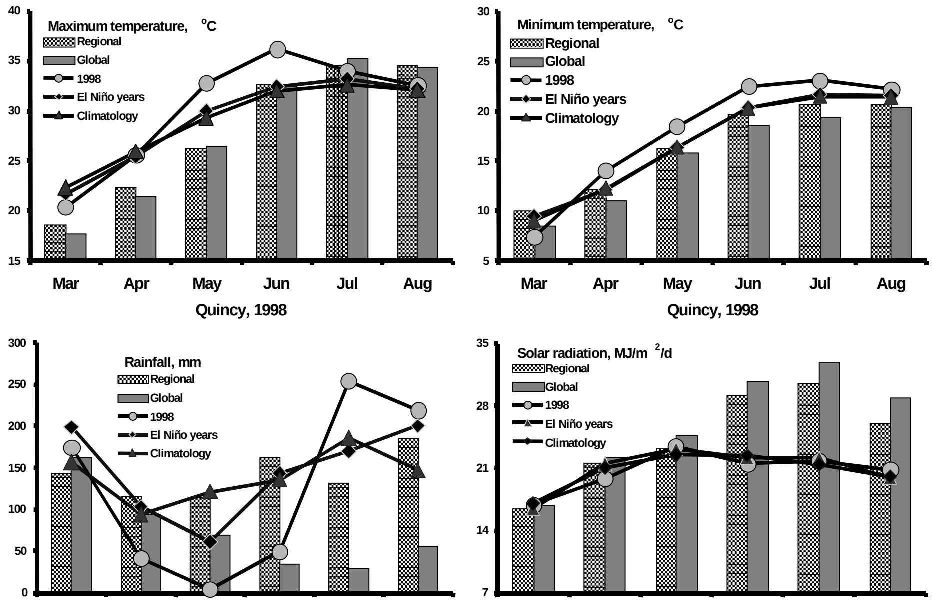

Figure 1. Monthly mean maximum and minimum temperatures (^oC), monthly total precipitation (mm) and monthly mean solar radiation (MJ m^{-2} d^{-1}) for 1998 from the global and regional models. Also shown are values corresponding to climatology (triangle), observations (circle) and average El Niño years. Figure reproduced from Jagtap et al. (2001b).

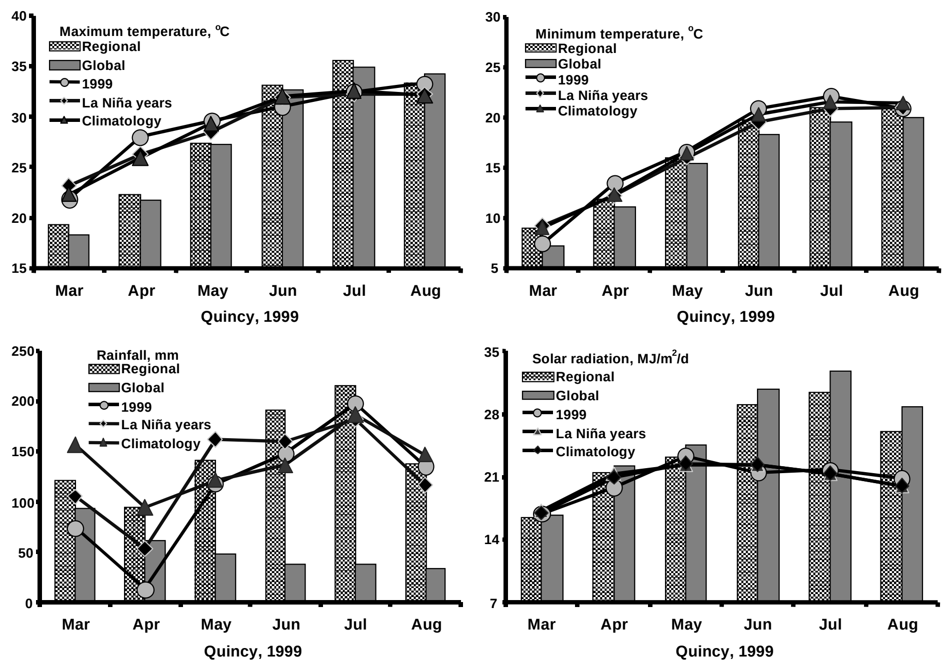

Figure 2. Monthly mean maximum and minimum temperatures (^oC), monthly total precipitation (mm) and monthly mean solar radiation (MJ m^{-2} d^{-1}) for 1999 from the global and regional models. Also shown are values corresponding to climatology (triangle), observations (circle) and average La Niña years. Figure reproduced from Jagtap et al. (2001b).

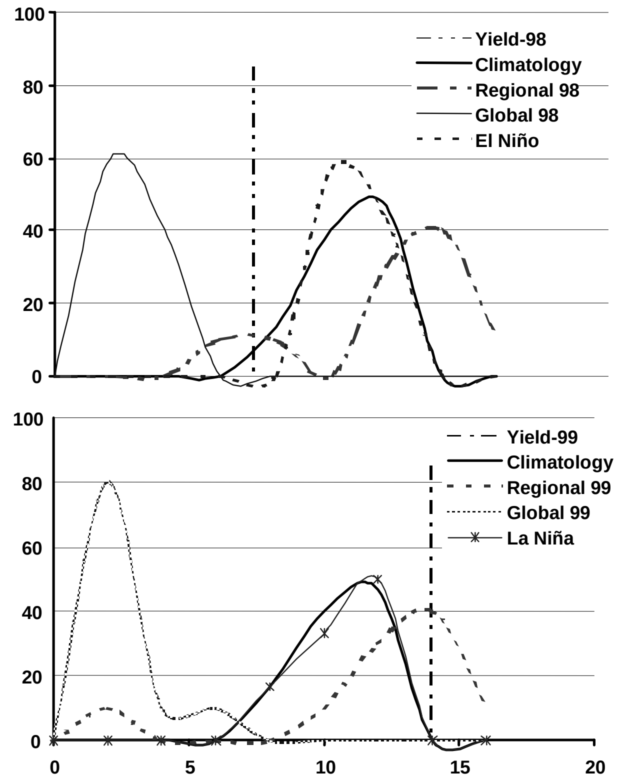

Figure 3. Relative frequency of maize yields forecast at Quincy, Florida, using different weather forecasting techniques and the current production practices for the (a) 1998 and (b) 1999 seasons. Yields were categorized into yield classes to create relative percentage values. More likely yields are indicated by higher percentages on the graphs. Figure reproduced from Jagtap et al. (2001b).

Table 1. Maize yield forecasted in 1998 and 1999 using different forecasting techniques and current management practices.

Forecast type	*n*	Mean Yield	Standard error	Prediction Mean Error	Minimum	Maximum	Expected yield*
		Mg/ha					
1998 weather	1	7.20 b					
Climatology	30	9.90 a	0.25	2.70	6.12	11.89	10-12
El Niño	7	10.31 a	0.37	3.11	9.10	11.84	8-10
Regional Model	10	11.00 a	0.99	3.80	4.66	14.17	12-14
1999 weather	1	13.94 b					
Climatology	30	9.90 a	0.25	-4.04	6.12	11.89	10-12
La Niña	6	9.96 a	0.61	-3.98	7.44	11.89	10-12
Regional Model	10	10.77 ab	1.26	-3.17	0.27	14.07	12-14

\+ Mean yields with no common letters differ significantly at the 0.05 probability level

* These values indicate lower and upper class limits

n Number of years of weather data or ensembles