REGIONAL ATMOSPHERIC CIRCULATION AND SURFACE TEMPERATURES PREDICTING COTTON YIELDS IN THE SOUTHEASTERN USA

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ABSTRACT

Research has shown strong relationships between ENSO phase and climate in the southeastern USA during the boreal winter. Crop yields in this region are significantly affected by ENSO phase due to predictable patterns of climate during this time of the year. However, both climate during the boreal summer months and cotton yields in this region show little or no association with ENSO phase. With a goal of improving prediction of cotton yields at a long lead-time in the SE USA, we identified regional atmospheric variables that are related to historic boreal summer rainfall and cotton yields, and evaluated the use of predictions of those variables from a global circulation model (GCM) for forecasting cotton yields. We analyzed de-trended cotton yields (1970-2004) from 48 counties in Alabama and Georgia, monthly rainfall from 53 weather stations, monthly estimates of 850 and 200 hPa winds at and surface temperatures over the SE USA region from reanalysis data, and monthly predictions of the same variables from the ECHAM 4.5 GCM. Meridional wind fields and surface temperature around SE USA were correlated with cotton yield and with rainfall, especially during April and July, over most of the region, explaining up to 52% of the inter-annual variability of observed yields. The tendency for cotton yields to be lower during years with atmospheric circulation patterns that favor higher humidity and rainfall is consistent with increased incidence of disease during flowering and harvest periods under wet conditions. Cross-validated yield predictions based on ECHAM hindcasts of wind and temperature fields forced by observed SSTs showed significant skill (55% hit skill based on terciles and 60% based on averages). Mean square errors of yield predictions varied from 3 to 10% over all locations and from 0 to 15% over all years. We conclude that there is potential to increase the skill of cotton yield forecasts using variables that are forecast by numerical climate models.

Key words: Boll rot, cotton, downscaling, global circulation model, hardlock of cotton, rainfall, yield forecast.

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INTRODUCTION

Previous research has shown strong relationships between phase of the El Niño-Southern Oscillation (ENSO) and climate in the southeastern United States of America (SE USA) during the boreal winter and spring months (Green et al., 1997; O'Brien et al., 1996, 1999; Ropelewski and Halpert, 1987; SRAT, 2002; Stahle and Cleaveland, 1992; Zorn and Waylen 1997). We have also shown that yields of some crops in this region are significantly affected by ENSO phase, such as tomato, wheat, and maize (Hansen et al., 1999, 2001) due to climate variability during this time of year. However, neither climate during the boreal summer months (Giannini et al., 2001; Higgins et al., 1998; Leathers, et al., 1991; Saravanan and Chang, 2000; Sutton et al., 2000; Ting et al., 1996) nor cotton yields in this region (Hansen et al., 2001) show significant association with the ENSO phase during the preceding boreal winter.

In 1997, cotton production was valued at $826 million in Alabama and Georgia (USDA/NASS 1997). In the last 15 years, cotton cultivation increased by 800 thousand hectares in the US, with much of the increase occurring in the Southeast. Yields have shown a positive trend during this period. US cotton exports more than doubled in the last 5 years (Goodman, 2004). Annual cotton lint yields and total production in Alabama and Georgia have shown considerable variability during the last 30 years (Figure 1). Figure 2 shows the locations and average yields of counties that have produced cotton consistently in the region.

Forecasts of boreal summer and fall climatic conditions and yields at a long lead time would allow farmers to adjust their management plans to reduce risks associated with climate variability (Baigorria, 2005; Hansen, 2005; Jagtap et al., 2002; Vedwan et al. 2005). Cotton yields can be decreased both by drought conditions and by diseases associated with wet and humid conditions during the harvest season of the six- to eight-week flowering window. Hardlock of cotton is mainly associated with the fungus *Fusarium verticillioides* (Marois et al., 2002), disease that causes fibers to bond into a hard shape instead of fluffing out as the boll opens and matures, thus reducing the amount of cotton harvested (Jost et al., 2005). In 2002, hardlock caused a 50% loss in yield (worth about $20 million) in the Panhandle of Florida. Boll rot, is caused by a complex of fungal and bacterial pathogens colonizing the cotton fiber during boll opening and harvesting periods (Jost el al., 2005; Marois et al., 2002).

The question addressed in this paper is whether a general circulation model (GCM), forced with sea surface temperatures (SSTs), can be used to predict rainfall and cotton yields in the SE USA. Weak predictability associated with ENSO in the SE USA during the summer growing season is the challenge. Teleconnection studies between ENSO and climate variability in the North Atlantic Ocean have demonstrated relationships only up to the Tropical Atlantic (Giannini et al., 2001; Higgins et al., 1998; Leathers et al., 1991; Saravanan and Chang, 2000; Sutton et al., 2000; Ting et al., 1996). Because a GCM integrates the influence of global SSTs, it may have potential to predict large-scale circulation patterns that influence local rainfall and crop yields better than statistical prediction from ENSO alone in this region of relatively weak predictability (Davis et al., 1997; Higgins et al., 1998; Stahle and Cleaveland, 1992).

The goal of this research is to evaluate the potential use of numerical climate forecasts from a GCM to predict yields of summer crops in the SE USA, early in the growing season. Specific objectives are to (a) evaluate the influence of regional atmospheric patterns on local rainfall and cotton yields, and (b) evaluate the potential use of a global circulation model (GCM), ECHAM v. 4.5, for predicting those regional atmospheric patterns and resulting cotton yields at a county scale in the SE USA.

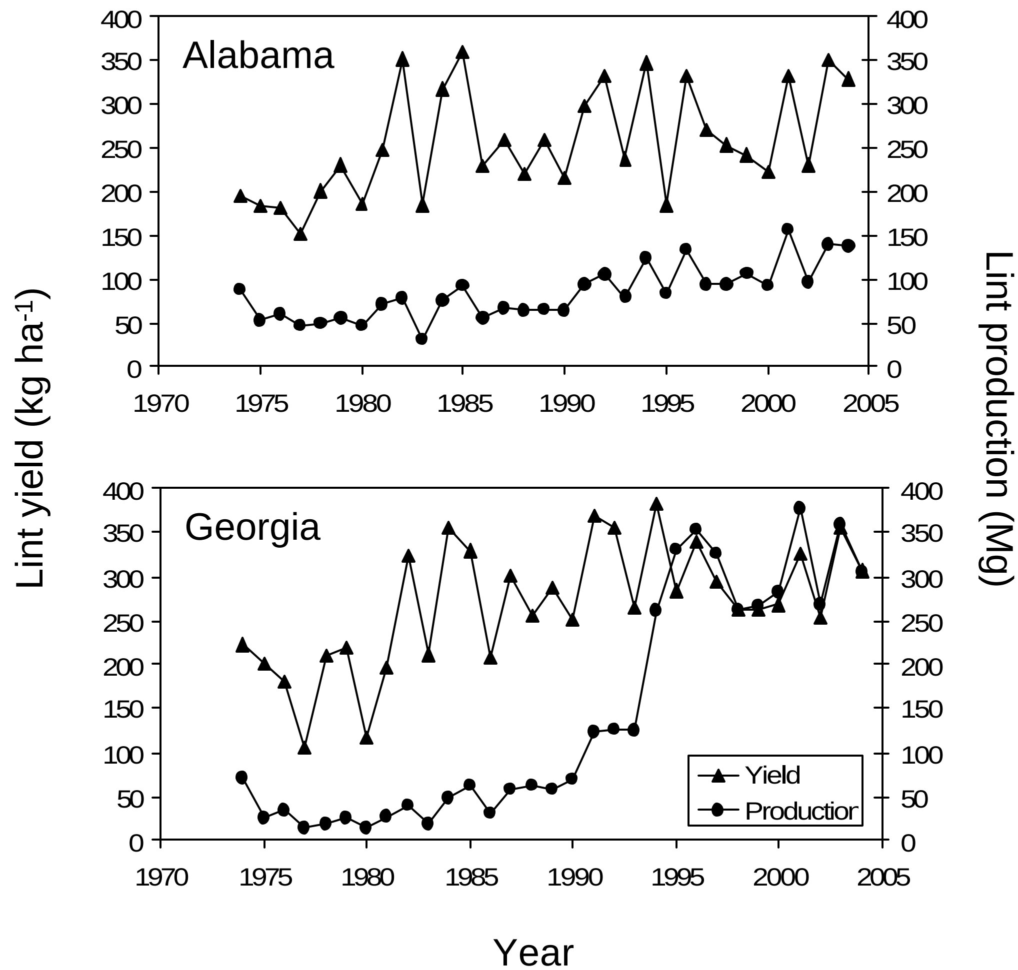

Fig. 1 Annual cotton yield and production in Alabama and Georgia.

METHODS

Data sources

Cotton yields. Cotton yield data from 48 counties in GA and AL with cotton production area 1,500 to 22,000 ha over the 35 years from 1974 through 2004 were obtained from the National Agricultural Statistics Service[‡] of the U.S. Department of Agriculture (Figure 2). These counties were selected because they have historical daily weather records for at least the last 35 years. One source of uncertainty is the lack of distinction in the production records between irrigated and rainfed areas as irrigation makes the crop less sensitive to variability in rainfall amounts.

[‡] http://www.usda.gov/nass/

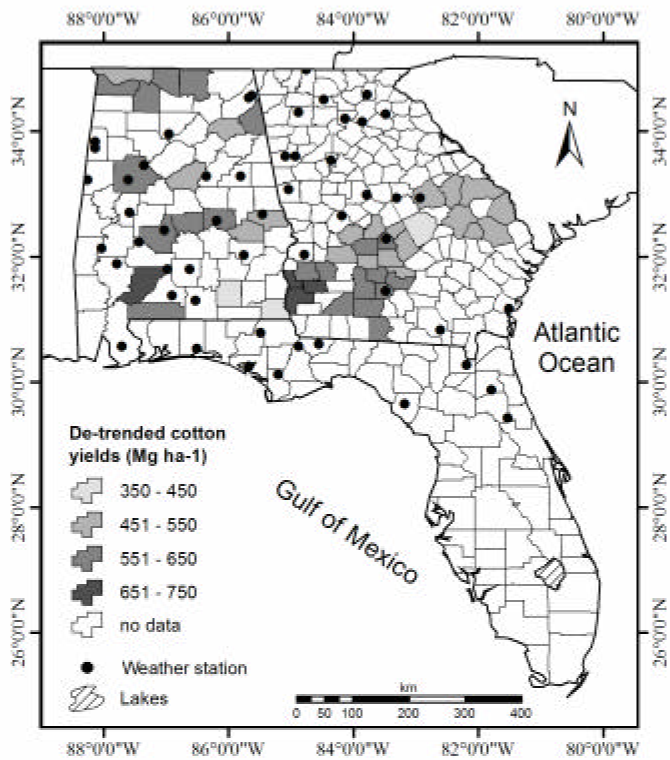

Fig. 2 Southeast U.S.A. showing location of the 53 weather stations and the 48 counties with the average de-trended cotton yield data used in this study.

Many non-climatic factors influence crop production, including changes in technology, land use (e.g., shifts between rainfed and irrigated production), soil quality, and market influences on input use and intensity of production. Analysis of agricultural time series data must first account for such trends. We assumed that climatic influences generally operate at a higher frequency than non-climatic influences. We used a low-pass spectral smoothing filter (Press et al., 1989) that removed a linear trend, applied a Fourier transformation, removed variations above a specified frequency, and then applied the inverse Fourier transformation and linear trend. Although the choice of smoothing period is subjective, we used a 10-year smoothing period based on experience with many crop data sets, thus avoiding removing annual fluctuations in yield associated with climate variability. Cotton yield residuals were calculated as:

$$y_{residual} = \frac{y_{observed}}{y_{trend}} - 1 \qquad \text{[Eq. 1]}$$

Climate. This study used three climate data sets from 1970 - 2004: daily rainfall from 53 weather stations (Figure 2) in the SE USA (National Climate Data Center[§]), monthly reanalysis data of wind fields at 850 hPa and 200 hPa, surface temperature (Kalnay et al., 1996), and monthly ECHAM-hindcast data for the same climate variables (Roeckner et al., 1996).

[§] http://nndc.noaa.gov/?home.shtml

Information from reanalysis and from ECHAM 4.5 was obtained from the International Research Institute for Climate and Society[†].

Initial conditions used by ECHAM 4.5 are sets of self-consistent model fields that come from previous integrations. We used the average of an ensemble of 24 model integrations. For these integrations the model initial conditions were generated slightly differently for 2 sets of members: (*i*) Members 1 to 8 were run by perturbing the initial atmospheric state and then spinning up the model for about 6 years to equilibrate the land surface model soil moisture; and (*ii*) Members 9 to 24 took the data from one of these previous realizations and added atmospheric noise about December 1949 to allow the models to diverge before the integrations started in January 1950. These simulations are not predictions because they used SST observations after the fact, and not predicted SSTs. They represent an upper bound on forecast skill since we can never achieve perfect SST forecasts.

The period from 1970 to 2004 was selected to avoid the effects of climatic change in rainfall regimens detected in the Panhandle of Florida, Southeastern Alabama and part of the Southwestern Georgia during the convective rainy season (Baigorria et al., submitted for publication). Monthly rainfall totals for each weather station were calculated from the daily values. The annual all-weather-station-average is shown in Figure 3.

Summarizing data by principle components. Principle component analysis is an effective method for summarizing correlated multivariate data. Principle components (PCs) are orthogonal linear transformations of a multivariate dataset that successively maximize the residual variance that remains after higher-order PCs. The first PC explains the greatest portion of variance, and therefore captures the dominant mode of variability. The transformation matrix consists of eigenvectors of the covariance matrix, where the sum of the squared annual weights equals 1 (Hair et al., 1998; Wilks, 1995). We used the first principle component (PC1) to spatially aggregate the time series of cotton yields from the 48 counties and observed rainfall from the 53 available stations in the study region. For gridded atmospheric variables from reanalysis and the GCM, we used a maximum of three principle components depending on the variable. Calculating PCs of rainfall from the correlation rather than covariance matrix avoided the problem of giving greater weight to locations with higher variance.

Association between cotton yields and climate

We used simple correlations between the first PCs of observed monthly rainfall and cotton yield residuals to evaluate the timing and magnitude of the relationship during the April to October growing season.

We then examined the strength and spatial patterns of correlation between regional climate variables and spatially aggregated cotton yield residuals. Monthly variables from reanalysis for each grid cell were averaged into April-June and July-September, corresponding to the early and late portions of the growing season. The split was performed for two reasons. First, weather conditions that favor early vegetative growth are different than those that favor flowering, boll formation and maturation. Second, the influence of ENSO on the region's climate may be different during the different periods. Maps of correlations between PC1 of cotton yield residuals and each grid cell of the reanalysis climate variables were examined for any spatial patterns that might suggest mechanisms.

[†] http://iridl.ldeo.columbia.edu/

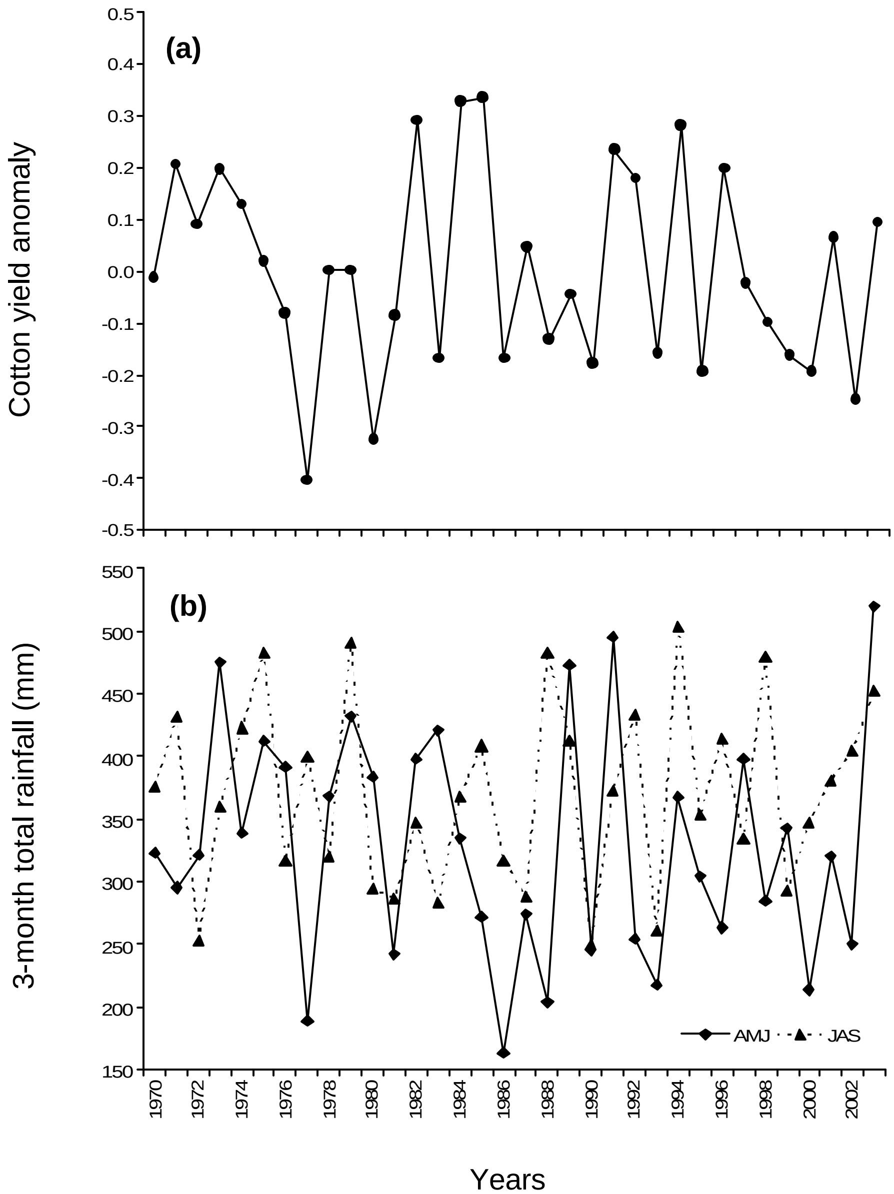

Fig. 3 Annual variability in cotton yield residuals averaged over all counties and annual variability of rainfall amounts averaged across all weather stations: (a) total rainfall in April, May, and June, and (b) total rainfall in July, August, and September.

Based on significant correlations of PC1 of cotton yield residuals with wind fields in the upper troposphere (200 hPa) and surface temperatures, further analyses focused on these two variables. To understand how these two atmospheric variables influence cotton yields, 200 hPa winds and surface temperatures from the five best years (1982, 1984, 1985, 1991, and 1994) and the five worst years (1977, 1980, 1990, 2000, and 2002) of de-trended cotton yields were averaged. Again, the cropping season was split between the April-June and July-September periods. To produce anomaly maps, we subtracted climatological averages from the eight composites: April-June and July-September winds and temperatures corresponding to the best and worst years.

Cotton yield residuals were predicted by canonical correlation analysis (CCA) using as predictors PCs of the regional temperature and circulation fields from reanalysis using leave-one-out cross-validation.

After determining that correlation between yield residuals and rainfall was strongest in July, we used the same procedure to investigate the relationship between local station precipitation and regional atmospheric circulation patterns. The years with the best and worst de-trended cotton yields do not coincide with the wettest and driest years (Figure 3). We prepared composite maps of upper tropospheric wind and surface temperature anomalies for the five wettest (1973, 1979, 1989, 1991, and 2003 for April-June; 1969, 1975, 1979, 1988, and 1994 for July-September) and five driest years (1977, 1986, 1988, 1993, and 2000 for April-June; 1972, 1981, 1983, 1990, and 1993 for July-September), just as we did for the years with the highest and lowest cotton yields.

Predicting cotton yield

After evaluating association between cotton yields and regional atmospheric circulation patterns from reanalysis data, we then evaluate the potential predictability of yield residuals, by using a GCM. To do this, monthly hindcasts of meridional winds at 200 hPa and surface temperatures during July-September for the same 35-year period were taken from ECHAM v. 4.5 simulations. Cotton yield residuals were predicted by CCA using as predictors PCs of the regional temperature and circulation fields from ECHAM 4.5 using leave-one-out cross-validation.

Initial diagnostics on the PCs of upper troposphere wind and surface temperature for April-June and July-September identified the first and third PCs of 200 hPa meridional winds and the first PC of surface temperatures for July-September as the best predictors of the first PC of cotton yield residuals. We used these variables to predict county yield residuals by cross-validated CCA using one CCA mode.

Analysis of predictability

Analyzes of predictability were performed by comparing the observed cotton yield residual versus both estimated cotton yield residuals (calculated by using reanalysis data and ECHAM 4.5 data). Two kinds of measures were used to analyze predictability. Measures based on continuous predictands were Pearson's correlation (r), Spearman's correlation (r_{rank}), and Mean Square Error (MSE), and a goodness-of-fit index (GFI) defined as the simple average of r across all counties. Measures based on categorical predictands were the hit score and hit skill score (Murphy, 1993).

The hit score is define as the percentage of times the forecast quantile category corresponds with the observed quantile category [Eq. 2], and the hit skill score was define as the percentage of times, beyond that expected by chance, the forecast quantile category corresponds with the observed quantile category [Eq. 3].

$$\text{Hit score} = \frac{\#\,\text{correct forecasts}}{\#\,\text{number of forecasts}} \times 100\% \qquad \text{[Eq. 2]}$$

$$\text{Hit skill score} = \frac{\#\,\text{correct} - \#\,\text{expected correct}}{\#\,\text{forecasts} - \#\,\text{expected correct}} \times 100\% \qquad \text{[Eq. 3]}$$

Hit score and Hit skill score were both based on terciles and on the average cotton yield residual. The hit skill score range from -100%, which indicates no predictability beyond random chance, to 100%, which indicates maximum predictability.

Observed and estimated all-county-average cotton yields were compared on an annual basis. The most accurately and least accurately predicted counties were also compared.

RESULTS AND DISCUSSION

Association between cotton yields and climate

The regional atmospheric variables with the highest correlations with cotton yields were meridional winds at 200 hPa and surface temperatures (Figure 4). The geographical areas shown in Figure 4 for each variable were selected when searching for the best prediction level using the CCA. From Figure 4a, positive values of meridional winds at 200 hPa (southern winds) are favorable to crop yields while negative values of meridional winds at the same altitude (northern winds) are unfavorable. Changes in wind direction are related in part to the location of the western sector of the North Atlantic Subtropical Anticyclone (Davis et al., 1997; Klein, 1957; Sahsamanoglou, 1990). From Figure 4b, low temperatures are favorable to crop yield while high temperatures are unfavorable.

Figure 5a shows wind anomalies in the upper troposphere and sea surface temperatures (SST) during the best and worst cotton yield years. During best cotton yield years, observed wind anomalies were from east to west in April-June, while during years of lowest cotton yields wind anomalies were from west to east. During July-September, wind anomalies changed from southeast to northeast, which is coherent to the previous correlations (Figure 4a).

Temperature and humidity from where the winds originate also help explain the relationships between regional climate patterns and cotton yields. During July-September, wind anomalies during the years having best cotton yields came from lower than normal SSTs in the Gulf of Mexico and the nearby Atlantic Ocean coast (Figure 6). During the worst cotton yield years, wind anomalies come from higher than normal SSTs from the Gulf of Mexico near the surface (850 hPa), and from the Great Lakes and the northern Atlantic Ocean coast in the upper troposphere (200 hPa). During the northern hemisphere summer (July-September), rainfall in the study area is dominated by convection triggered by warm ground surfaces, and thus has low spatial correlation (Baigorria et al., submitted). Air mass advection transports atmospheric temperature and humidity, which can either intensify or decrease convective rainfall. In the best cotton yield years, air with lower than normal temperatures carried from the Gulf of Mexico and the nearby Atlantic Ocean coast has higher density, resulting in increased subsidence of the upper air mass. This subsidence is unfavorable to convective cloud growth. During the worst cotton yield years, air with warmer than normal temperatures from the Gulf of Mexico near the surface and from the Great Lakes and northern Atlantic Ocean coast in the upper troposphere has lower density, increasing the convective activity in the study area. Although in both cases low altitude advection is from a water source, differences in air mass temperature result in different absolute humidity. This means that during the worst cotton yield years, warmer than normal conditions are associated with increased water available for condensation relative to the best cotton yield years. This difference in humidity influences the important cotton diseases, hardlock and boll rot. The inverse relationship between surface temperature and the PC1 cotton yield (Figure 4b) supports this hypothesis.

For 74% of the counties, station rainfall showed the strongest association with cotton yields (GFI = 0.485) in July (Table 1). Fewer counties showed significant yield correlations with rainfall in August or September, maybe due to later planting dates. We suspect that the five counties that showed no significant correlation between cotton yields and rainfall in any month may have had a high percentage of fields under irrigation. In the SE USA, cotton is usually planted between early April and late May. Early planting dates ensure enough rainfall during the cropping season, but with higher risk of diseases during the rainy season of July-September, especially during highly active hurricane seasons.

Among the regional atmospheric variables that we considered, meridional winds at 850 hPa showed the highest correlations with July rainfall. The geographical area shown in Figure 7 was selected when searching for the best prediction level of July rainfall using the CCA.

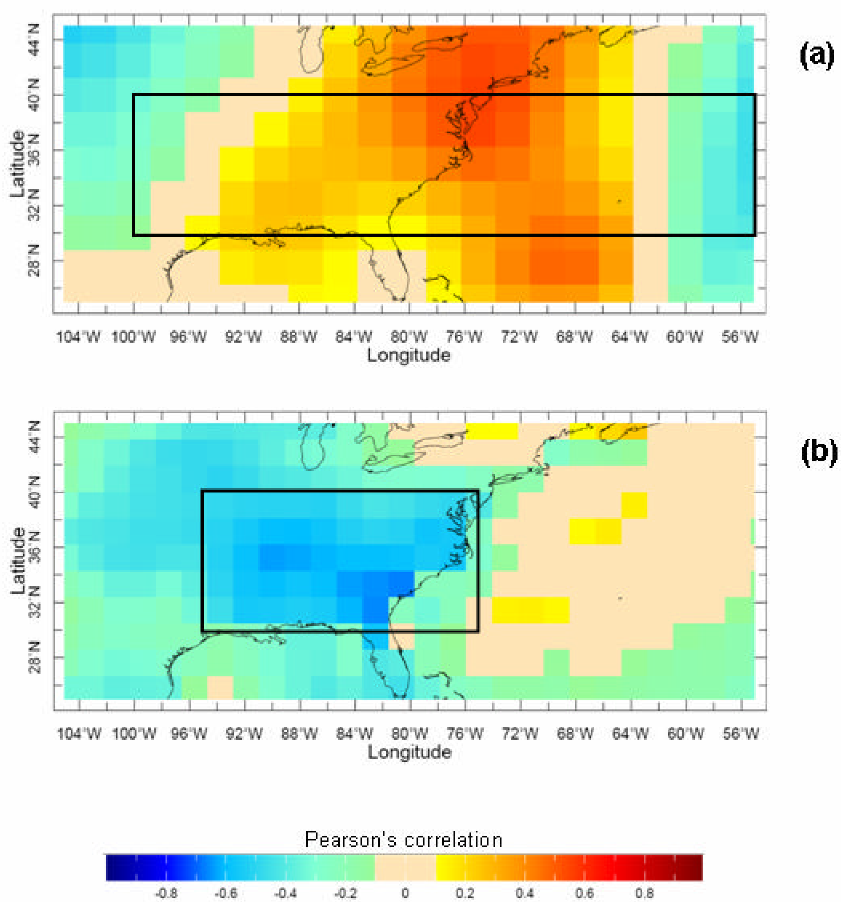

Fig. 4 Correlation maps between the EOF of observed cotton yield residuals and (a) Meridional winds at 200 hPa, or (b) Surface temperature.

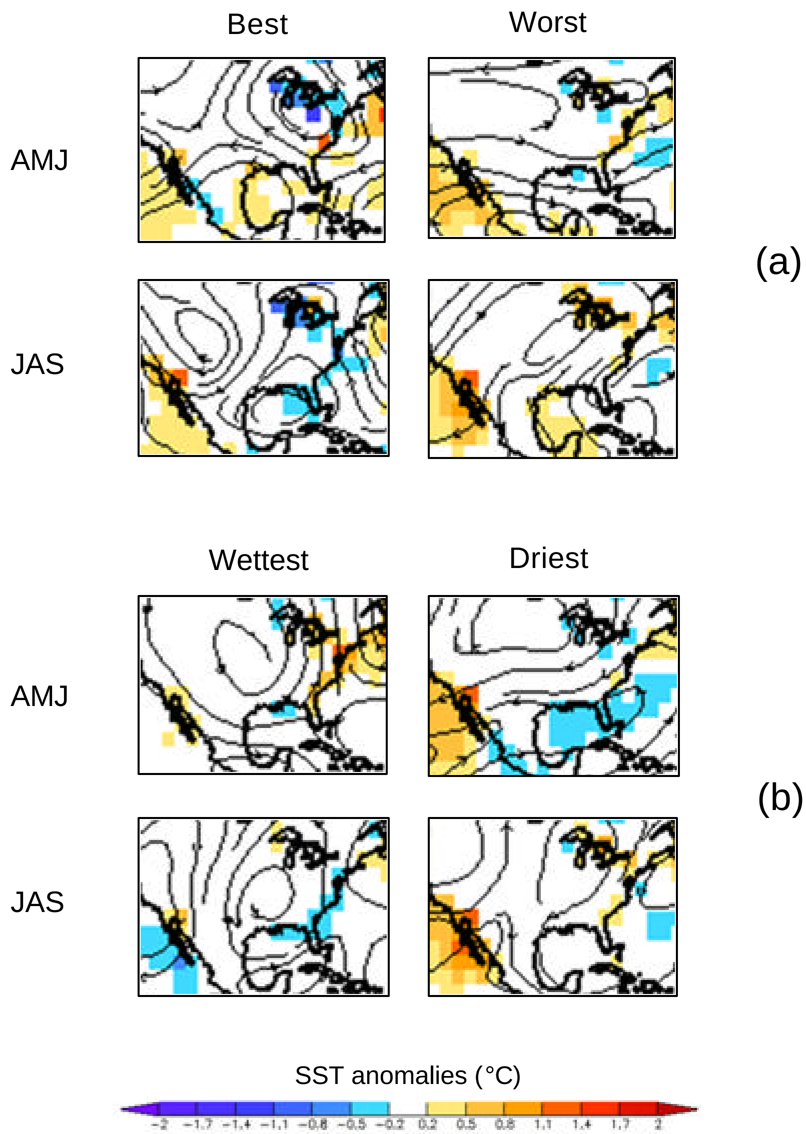

Fig. 5: Anomalies of sea surface temperature and wind fields in the upper troposphere (200 hPa). Observed (reanalysis) and hindcasted (ECHAM) values during the periods April-June and July-September for the five best and five worst years of cotton yields and for the wettest and driest five years.

During the five years with highest July rainfall, observed wind anomalies came from the southwest (Figure 5b). During the years with lowest July rainfall, wind anomalies came from the northeast for both April-June and July-September. These patterns are different from the ones shown during the best and worst years of cotton yields (Figure 5a). The relationship between wind direction and rainfall regimes agree with the annual migration of the subtropical anticyclone over the North Atlantic (Davis et al., 1997; Stahle and Cleaveland, 1992). Analyses revealed that cotton yields were not predictable from 850 hPa meridional winds (data not shown). We therefore selected meridional winds at 200 hPa and surface temperatures as atmospheric predictors of cotton yields.

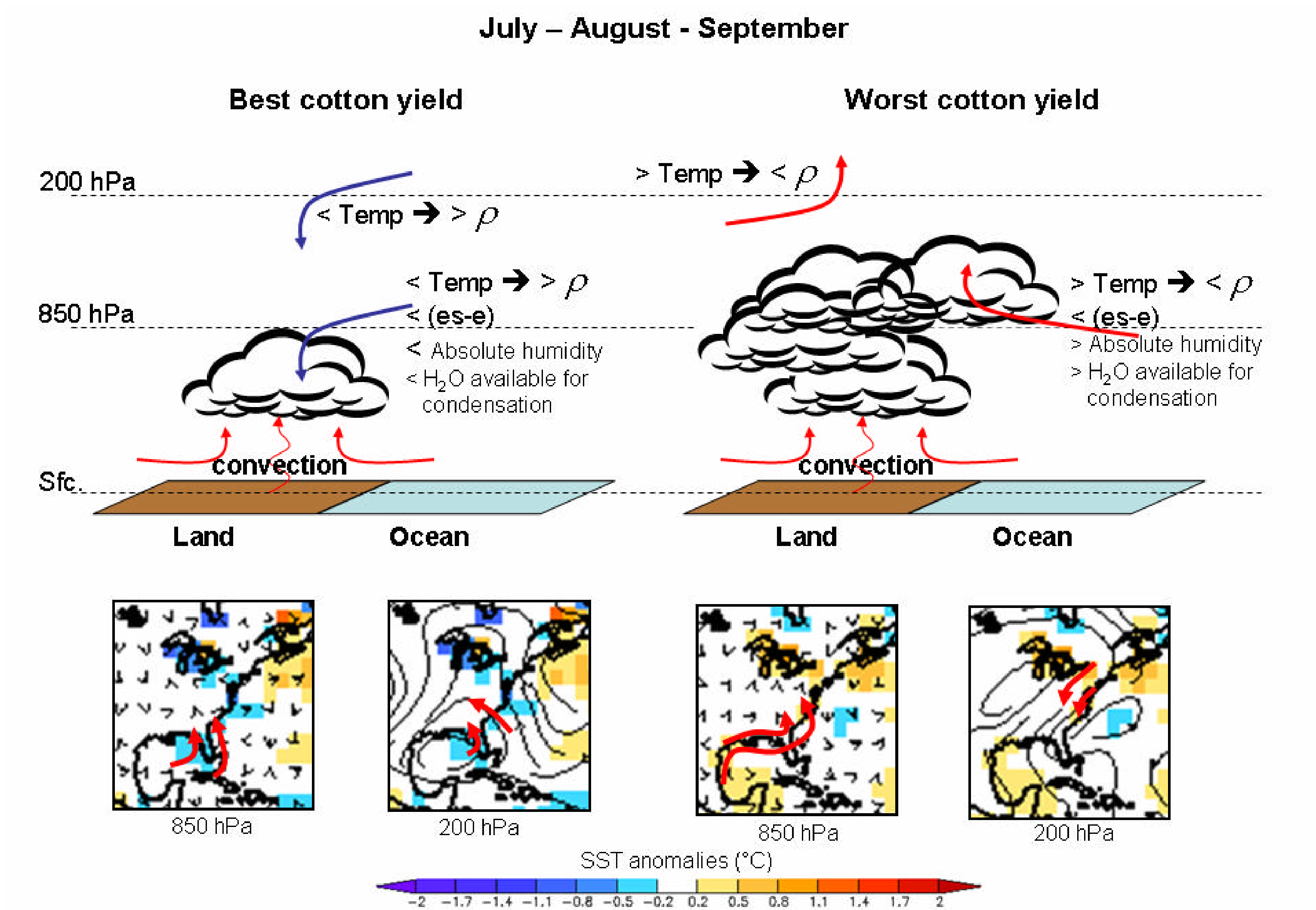

Fig. 6: Effect of Wind and sea surface temperature anomalies in cotton yields. Wind field anomalies at 850 hPa and 200 hPa, and sea surface temperature anomalies during the best and worst 5 years of cotton production.

Table 1 Goodness-of-Fit index (GFI) of the cross validation analysis over 53 counties between the observed cotton yield residuals and the estimated cotton yield residuals using monthly rainfall as predictors.

Months	GFI	Percent of counties significant at:		
		a = 0.01	a = 0.05	ns
April	-0.101	0	0	100
May	-0.117	0	0	100
June	-0.042	0	0	100
July	0.485	69	15	16
August	0.132	2	11	87
September	0.098	2	6	92
October	0.042	0	0	100

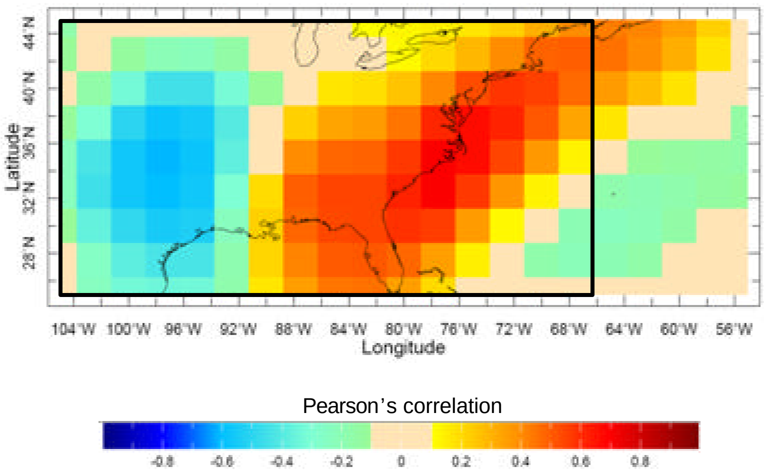

Fig. 7: Correlation maps between the EOF of the observed July rainfall and Meridional winds at 850 hPa.

Predicting cotton yields

Figure 8 compares de-trended cotton yields with cross-validated predictions based on upper troposphere wind and surface temperature fields from both reanalysis and from ECHAM 4.5, for averages across counties, and for the best- and the worst-predicted counties. Reanalysis data provided reasonable predictions ($p<0.01$) of average total production yields across counties (Figure 8a) and for the best-predicted county (Figure 8b). The one notable exception, 1977, was one of the most severe droughts in the last 50 years in the SE USA. The average cotton yield was relatively low (ranked 46th out of 48 counties) in the best-predicted county (Laurens), while the highest-yielding county (Clay) showed the weakest predictability from reanalysis variables. This is consistent with our speculation that climate-based yield predictability is weaker in counties with greater proportion of cultivated areas under irrigation, but data are not available to test this. Differences in soils, management or climate may also account for the differences in yields. There is a weak tendency for higher correlations to be associated with lower average yields.

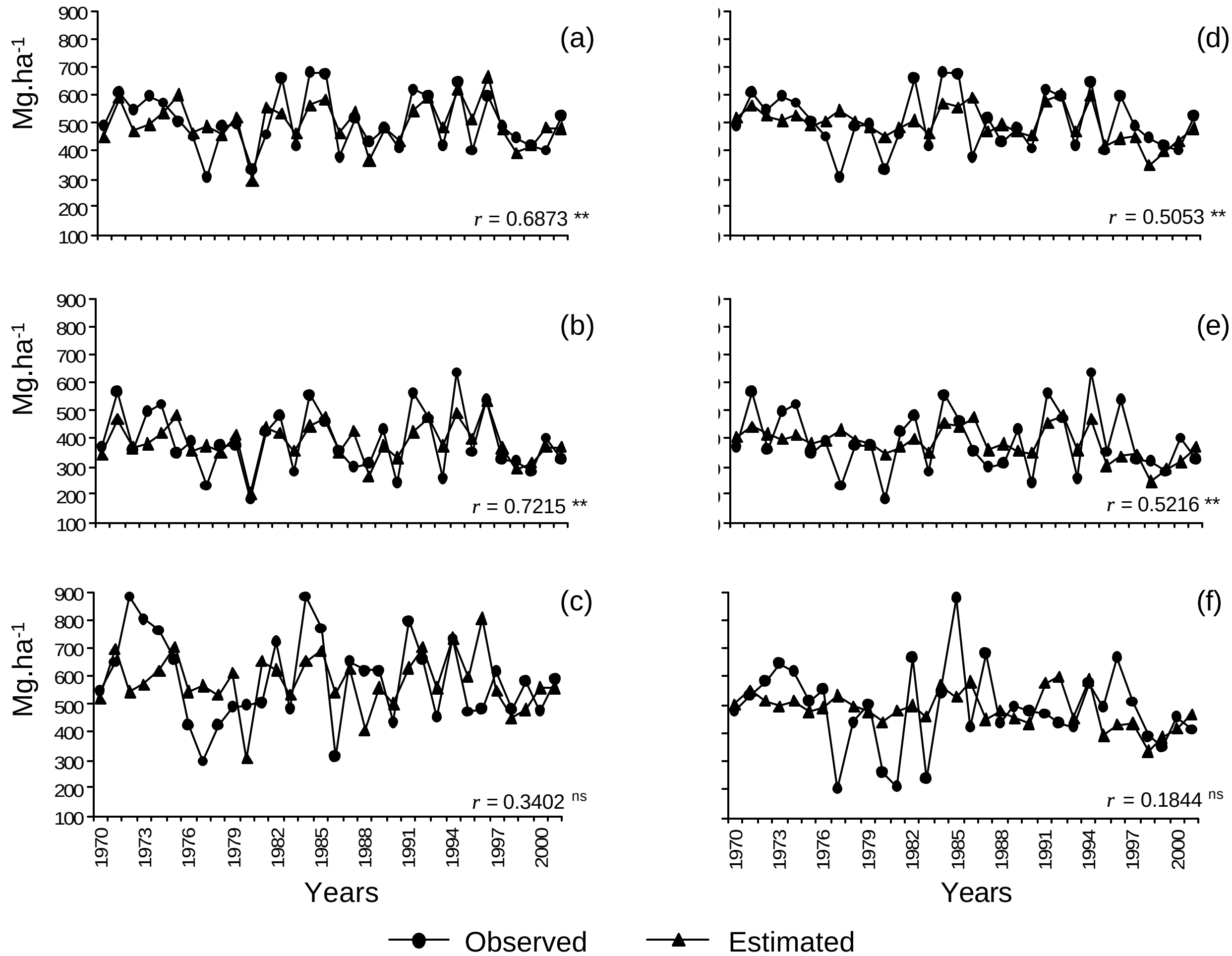

Fig. 8 Comparison of annual variability in observed de-trended yield with predicted de-trended yield using predictors from reanalysis data: (a) Mean over all counties; (b) best predicted county, Laurens, GA; and (c) worst predicted county, Clay, GA, and from ECHAM 4.5 hindcast made each year between February and April. (d) Mean over all counties, (e) best predicted county, Laurens, GA, and (f) worst predicted county, Sumter, GA. ** Significant at p<0.01. ns = non significant.

Reanalysis meridional winds in the upper atmosphere combined with surface temperatures during July-September explained up to 52% of the total yield variability in specific counties (Appendix 1). In 47 of the 48 counties, ρ was statistically significant, with 67% of the counties statistically significant at α=0.01 and 31% statistically significant at α=0.05. Values of ρ and ρrank were similar, suggesting that the climate drivers were not influenced seriously by extreme data (e.g., hurricanes). In all cases, cotton yield predictability as measured by hit skill scores was better than chance. The spatial distribution of hit skill score based on terciles (Figure 9) is related to the quality of the crop yield information. As mentioned before, the statistics used in this study do not distinguish between irrigated and rainfed areas, early and late planting dates, or short- and long-season cultivars. We expect predictability to be higher in predominantly rainfed than in predominantly irrigated areas.

Although rainfall during April-June was not a useful predictor of cotton yields, zonal (west-east) winds at 200 hPa could predict part of the April rainfall variability in the SE-USA (GFI=0.309), during the time when most of the summer crops are planted.

Yields averaged across counties also showed significant predictability ($p<0.01$) from atmospheric fields simulated by ECHAM 4.5 (Figure 8d). As expected, the general predictability of yields from the GCM was lower than that based on the reanalysis data. However, 22% of the Counties in Alabama increased values of ρ (Appendix 1 and 2) and 50% increased values of hit skill score based on terciles (Figure 9). Based on hit skill scores, predictability was still better than chance except in one county. The categorical measures of forecast accuracy based on terciles gave hit score values ranging between 70% and 30% and between 55% and -9% for hit skill score. Categorical measures of forecast accuracy based on average gave better results, with hit score values ranging from 81% to 53% and hit skill score ranging from 60% to 8%. Based on r, the percentage of counties with statistically significant predictability changed to 23% ($p<0.01$) and 35% ($p<0.05$) compared to those obtained from the reanalysis climate data: 66% ($p<0.01$) and 31% ($p<0.05$).

ECHAM 4.5 failed to predict the low yields observed in 1977, 1980, and 1986. Regional atmospheric variables from reanalysis data also did not predict the low yield associated with the 1977 drought (Figure 8). The correlation ranking of counties differed between predictions based on ECHAM 4.5 and predictions based on reanalysis (Appendix 1 and 2). Predictability of cotton yields in individual counties tended to be weaker than the predictability of the average across counties, with correlations ranging from 0.52 in Laurens County to 0.18 in Sumter County, both in Georgia (Figure 8e, f). Observed yields in Sumter County show lower mean and higher inter-annual variability than the all-county average.

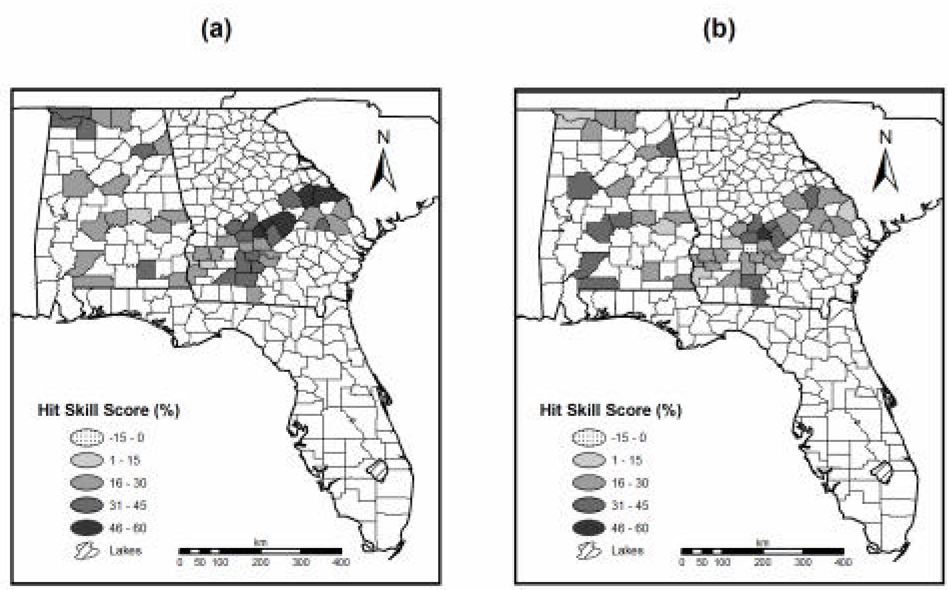

Fig. 9 Spatial distribution of forecast hit skill score using: (a) reanalysis climate predictors, and (b) ECHAM 4.5 hindcast made each year between February and April.

Our ability to predict cotton yields is not directly related to our ability to predict rainfall amounts using reanalysis data. Comparisons between Figures 9a and 10 shows that while the best cotton yields were predicted in central and eastern Georgia (Figure 9), the best July rainfall predictions occurred in central and eastern Alabama and northwestern Georgia (Figure 10). Although meridional winds at 850 hPa predicted July rainfall better than winds at 200 hPa, meridional winds near surface did not contribute significantly to prediction skill for cotton yields. This supports the hypothesis that cotton yields were affected not only by rainfall but also by variables such as temperature and humidity.

The prediction of cotton yields in this study is related to predictable variations in rainfall and humidity both through their effect on drought stress, and through stress caused by diseases associated with wetness. Water availability, as influenced by the amount and frequency of precipitation, is particularly important during anthesis and boll maturation, especially in sandy soils with low water retention. Irrigation during these critical periods usually increases yields (Jost et al., 2005; Marois et al., 2004). However, the same amount of water applied as rainfall may increase the risk of diseases. These contrasting effects of wetness on cotton production make it difficult to forecast yield directly from seasonal rainfall totals alone. Further work is needed to distinguish rainfall effects on crop water stress and diseases. Dynamic crop models (Jones et al., 2003) are useful for this kind of analysis.

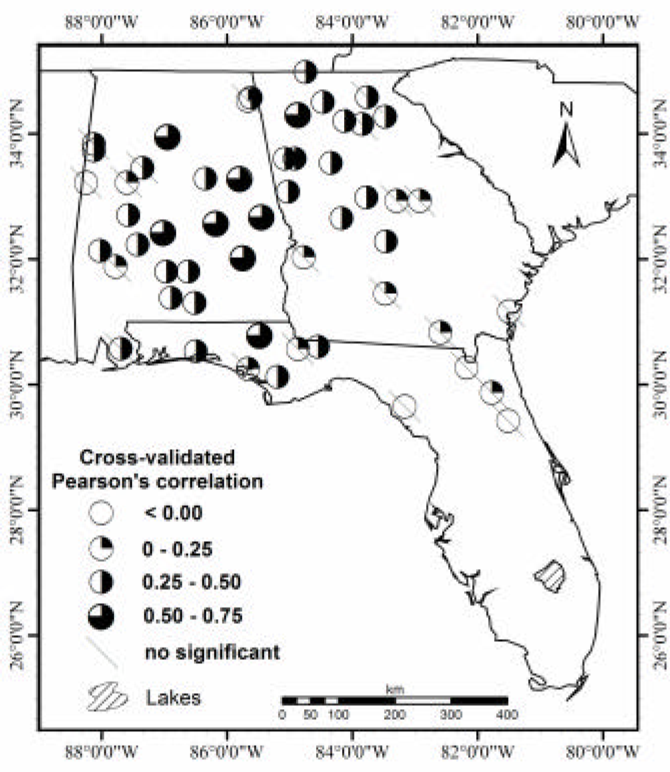

Fig. 10 Spatial distribution of the cross-validated Pearson's correlation between observed July rainfall and estimated July rainfall using meridional winds at 850 hPa as the predictor.

The results demonstrate the ability of a GCM that is used operationally for seasonal climate prediction to simulate regional atmospheric features, such as upper tropospheric winds and surface temperatures, which influence cotton yields in the SE USA. However, the ECHAM 4.5 simulations are not true predictions because the model is forced with observed and not predicted SSTs. The cotton yield results therefore represent an upper bound of predictability from the GCM forced with SST boundary conditions. Assessing operational predictability of cotton yields with the GCM will require consideration of the influence of the various methods for predicting SSTs.

CONCLUSIONS

Specific atmospheric circulation patterns that favor high humidity, temperature and rainfall during summer are associated with low cotton yields in the SE-USA, consistent with the tendency of humid conditions and wet foliage to favor increased incidence of diseases during flowering and maturation. Up to 52% of the inter-annual variability of lint yield in specific counties is explained from observed meridional winds at 200 hPa and surface temperatures. The same climatic predictors are significantly correlated with April and July rainfall in most of the study area. Although rainfall during this period seems relevant to the management of summer crops, the ability of the GCM to capture cotton yields was not based entirely on its ability to simulate local rainfall, and was not related to rainfall prediction early in the growing season. Cotton yields predicted from ECHAM 4.5 forced by observed SSTs represent an upper bound of predictability using this GCM. Although the predictability of yields using the GCM was lower than that based on reanalysis data, 58% of the counties showed statistically significant ($p<0.05$) potential predictability based on continuous measures. Categorical measures of yield predictability exceeded chance in 98% of the counties. There is a physical and biological relationship between cotton yield, and regional atmospheric circulation and surface temperatures. However evaluation of the predictability of lint yields that can be obtained operationally will require evaluation of several GCMs forced by SSTs predicted by several available methods. Linking crop models to global seasonal climate forecast like the one used here, or high-resolution regional models tailored to the specific region (Cocke and LaRow, 2000; Shin, et al., 2005), appears to have potential for forecasting cotton yield at a long lead time, and might provide a basis for exploring management alternatives to reduce risk and enhance profitability.

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Appendix 1 Main statistics of the cross validation analysis by county for cotton yield residuals predicted by observed meridional winds in the upper troposphere and surface temperatures.

County, State	r	r_{rank}	MSE	Based on terciles: Hit Score (%)	Based on terciles: Hit Skill Score (%)	Based on average: Hit Score (%)	Based on average: Hit Skill Score (%)
Laurens, GA	0.7215 **	0.6620	0.04	68.8	53.1	78.1	46.2
Bleckley, GA	0.7211 **	0.6671	0.04	68.8	53.1	87.5	66.7
Dooly, GA	0.6911 **	0.6811	0.06	59.4	39.1	78.1	53.3
Burke, GA	0.6772 **	0.7155	0.06	68.8	53.1	78.1	46.2
Macon, GA	0.6640 **	0.6210	0.05	56.3	34.4	78.1	58.8
Jefferson, GA	0.6287 **	0.6111	0.06	68.8	53.1	75.0	50.0
Dodge, GA	0.6258 **	0.6081	0.04	59.4	39.1	71.9	40.0
Emanuel, GA	0.6118 **	0.5777	0.05	53.1	29.7	71.9	47.1
Crisp, GA	0.5977 **	0.5976	0.04	46.9	20.3	87.5	71.4
Terrell, GA	0.5804 **	0.6525	0.03	46.9	20.3	81.3	62.5
Pulaski, GA	0.5784 **	0.5770	0.06	65.6	48.4	68.8	44.4
Colquitt, GA	0.5778 **	0.6515	0.03	62.5	43.8	84.4	73.7
Worth, GA	0.5753 **	0.6057	0.03	56.3	34.4	84.4	61.5
Washington, GA	0.5746 **	0.5832	0.07	56.3	34.4	81.3	50.0
Coffee, AL	0.5740 **	0.6246	0.04	56.3	34.4	84.4	70.6
Screven, GA	0.5712 **	0.5701	0.05	50.0	25.0	68.8	28.6
Houston, GA	0.5645 **	0.6170	0.06	62.5	43.8	75.0	42.9
Madison, AL	0.5544 **	0.5355	0.04	53.1	29.7	71.9	40.0
Turner, GA	0.5309 **	0.5843	0.06	56.3	34.4	81.3	57.1
Tift, GA	0.5209 **	0.5520	0.03	56.3	34.4	78.1	53.3
Lauderdale, AL	0.5168 **	0.5312	0.04	56.3	34.4	75.0	38.5
Monroe, AL	0.5082 **	0.5091	0.03	50.0	25.0	75.0	42.9
Wilcox, GA	0.5000 **	0.5274	0.05	53.1	29.7	78.1	46.2
Etowah, AL	0.4993 **	0.4454	0.08	56.3	34.4	68.8	37.5
Cherokee, AL	0.4989 **	0.4600	0.08	53.1	29.7	65.6	35.3
Randolph, GA	0.4977 **	0.6052	0.05	50.0	25.0	84.4	66.7
Candler, GA	0.4921 **	0.4366	0.06	56.3	34.4	62.5	25.0
Limestone, AL	0.4905 **	0.4952	0.05	50.0	25.0	68.8	28.6
Colbert, AL	0.4777 **	0.5029	0.05	59.4	39.1	75.0	42.9
Lee, AL	0.4676 **	0.4312	0.04	46.9	20.3	65.6	15.4
Ben Hill, GA	0.4642 **	0.4446	0.06	46.9	20.3	78.1	53.3
Sumter, GA	0.4504 **	0.4967	0.07	50.0	25.0	75.0	50.0
Dallas, AL	0.4454 *	0.5239	0.04	50.0	25.0	65.6	35.3
Macon, AL	0.4378 *	0.3985	0.05	50.0	25.0	68.8	28.6
Lawrence, AL	0.4356 *	0.5209	0.05	56.3	34.4	65.6	15.4
Elmore, AL	0.4331 *	0.4257	0.05	37.5	6.3	65.6	35.3
Bulloch, GA	0.4240 *	0.4256	0.06	50.0	25.0	62.5	25.0
Mitchell, GA	0.4154 *	0.5242	0.04	56.3	34.4	59.4	27.8
Irwin, GA	0.4096 *	0.4787	0.05	50.0	25.0	68.8	44.4
Early, GA	0.3963 *	0.5221	0.04	43.8	15.6	75.0	50.0
Brooks, GA	0.3935 *	0.5326	0.02	43.8	15.6	78.1	58.8
Tuscaloosa, AL	0.3903 *	0.4725	0.04	46.9	20.3	78.1	53.3
Calhoun, GA	0.3811 *	0.4405	0.03	40.6	10.9	75.0	50.0
Escambia, AL	0.3717 *	0.3943	0.03	50.0	25.0	62.5	25.0
Houston, AL	0.3652 *	0.3756	0.07	43.8	15.6	68.8	23.1
Autauga, AL	0.3589 *	0.4501	0.05	53.1	29.7	75.0	50.0
Shelby, AL	0.3585 *	0.3966	0.04	43.8	15.6	65.6	35.3
Clay, GA	0.3402	0.4707	0.07	37.5	6.3	68.8	37.5

*, ** Significant at $p<0.05$ and $p<0.01$, respectively.

Appendix 2 Main statistics of the cross validation analysis by county for annual cotton yield residuals predicted by hindcast meridional winds in the upper troposphere and surface temperatures.

County, State	r	r_{rank}	MSE	Based on terciles: Hit Score (%)	Based on terciles: Hit Skill Score (%)	Based on average: Hit Score (%)	Based on average: Hit Skill Score (%)
Laurence, GA	0.5216 **	0.5211	0.06	48.5	22.7	68.8	23.1
Autauga, AL	0.5143 **	0.5368	0.04	57.6	36.4	71.9	43.8
Dooly, GA	0.5034 **	0.4940	0.08	54.5	31.8	81.3	60.0
Dodge, GA	0.5004 **	0.5388	0.05	57.6	36.4	75.0	46.7
Bleckley, GA	0.4850 **	0.4463	0.06	54.5	31.8	71.9	25.0
Wilcox, GA	0.4722 **	0.4588	0.05	48.5	22.7	75.0	38.5
Dallas, AL	0.4611 **	0.4894	0.04	57.6	36.4	62.5	29.4
Emanuel, GA	0.4546 **	0.4475	0.07	48.5	22.7	68.8	41.2
Coffee, AL	0.4405 **	0.4592	0.06	48.5	22.7	59.4	23.5
Candler, GA	0.4374 **	0.4659	0.06	45.5	18.2	75.0	50.0
Monroe, AL	0.4301 **	0.4491	0.03	57.6	36.4	75.0	42.9
Ben Hill, GA	0.4265 *	0.4052	0.06	48.5	22.7	81.3	60.0
Macon, AL	0.4185 *	0.4586	0.05	42.4	13.6	78.1	50.0
Houston, GA	0.4077 *	0.4789	0.08	60.6	40.9	71.9	35.7
Washington, GA	0.4061 *	0.5007	0.08	48.5	22.7	71.9	25.0
Lee, AL	0.3991 *	0.4287	0.04	45.5	18.2	68.8	23.1
Worth, GA	0.3947 *	0.4092	0.04	51.5	27.3	75.0	38.5
Macon, GA	0.3927 *	0.4050	0.07	48.5	22.7	68.8	41.2
Escambia, AL	0.3915 *	0.4139	0.03	54.5	31.8	68.8	37.5
Pulaski, GA	0.3862 *	0.4208	0.08	69.7	54.5	71.9	50.0
Madison, AL	0.3832 *	0.3475	0.05	48.5	22.7	62.5	20.0
Houston, AL	0.3780 *	0.4279	0.07	45.5	18.2	71.9	30.8
Clay, GA	0.3730 *	0.4134	0.06	48.5	22.7	65.6	31.3
Tuscaloosa, AL	0.3725 *	0.4362	0.04	57.6	36.4	68.8	33.3
Calhoun, GA	0.3715 *	0.4909	0.03	51.5	27.3	68.8	37.5
Colquitt, GA	0.3656 *	0.4359	0.04	54.5	31.8	62.5	36.8
Limestone, AL	0.3580 *	0.3707	0.06	48.5	22.7	65.6	21.4
Crisp, GA	0.3486 *	0.4195	0.06	30.3	-9.1	71.9	35.7
Etowah, AL	0.3432	0.4037	0.09	51.5	27.3	65.6	31.3
Colbert, AL	0.3335	0.3650	0.06	42.4	13.6	65.6	21.4
Early, GA	0.3328	0.3564	0.04	36.4	4.5	71.9	43.8
Brooks, GA	0.3279	0.2670	0.02	54.5	31.8	56.3	17.6
Elmore, AL	0.3264	0.3642	0.06	48.5	22.7	68.8	41.2
Cherokee, AL	0.3196	0.3486	0.09	57.6	36.4	68.8	41.2
Tift, GA	0.3173	0.3452	0.04	42.4	13.6	68.8	33.3
Turner, GA	0.3109	0.3720	0.07	45.5	18.2	78.1	50.0
Bulloch, GA	0.2976	0.3142	0.07	51.5	27.3	71.9	43.8
Burke, GA	0.2947	0.3536	0.10	51.5	27.3	68.8	23.1
Terrell, GA	0.2906	0.4071	0.05	45.5	18.2	65.6	31.3
Lawrence, AL	0.2808	0.3469	0.06	51.5	27.3	62.5	7.7
Lauderdale, AL	0.2665	0.2931	0.06	42.4	13.6	62.5	7.7
Randolph, GA	0.2659	0.3432	0.06	51.5	27.3	68.8	33.3
Jefferson, GA	0.2634	0.2874	0.10	57.6	36.4	65.6	31.3
Screven, GA	0.2588	0.2324	0.08	36.4	4.5	65.6	21.4
Irwin, GA	0.2392	0.2767	0.05	51.5	27.3	53.1	16.7
Shelby, AL	0.2262	0.2540	0.05	45.5	18.2	59.4	23.5
Mitchell, GA	0.2027	0.3000	0.05	45.5	18.2	53.6	22.2
Sumter, GA	0.1844	0.2226	0.09	42.4	13.6	59.4	18.8

*, ** Significant at p<0.05 and P<0.01, respectively.