Forecasting Cotton Yield in the Southeastern United States using Coupled Global Circulation Models

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Agroclimatology

ABSTRACT

We developed methods of forecasting cotton (*Gossypium hirsutum* L. var. *hirsutum*) yields at a county level 3 mo before harvest for the states of Alabama and Georgia. Cotton yield historical records for 57 counties were obtained from NASS and detrended using a low-pass spectral filter. A Canonical Correlation Analysis regression-based model was annually recalibrated to incorporate the year-by-year accumulating data: (i) April–June (during vegetative growth) observed rainfall for the forecasting year, and (ii) July–September (during reproductive growth) global-scaled 2-m mean temperatures for years before the forecasting year, beginning with 1970. We produced two types of forecasts: short range and medium range. The short-range near-term yield forecast (just before initiating harvest in the region) used gridded assimilated observed 2-m mean temperatures obtained from the NCEP-NCAR CDAS Reanalysis data. The medium-range forecast (3 mo before harvest) used 2-m mean temperature retrospective forecasts from the operational NOAA/NWS/NCEP Climate Forecasts System coupled global circulation model. The short-range, near-term forecast performance was measured by leave-one-out cross-validation and retroactive validation, whereas medium-range forecast performance used the previous two methods plus a proposed coral-reef validation method. The agreement between short-range near-term forecast and actual cotton yield was statistically significant at the 0.05 level in 31 out of 57 counties. For 48% of these 31 counties, the agreements between medium-range forecasts and actual cotton yields were statistically significant at the 0.05 level. The goodness-of-fit index for those 15 counties was 0.51 and the RMSE ranged from 13 to 31% of the annual yield.

Interannual variability of the seasonal climate greatly affects agriculture, generating uncertainties that often concerns policymakers at district, watershed, national, or broader levels (Hansen and Jones, 2000). In the last two decades, dynamic crop models (e.g., Jones et al., 2003) have been used in translating climate variability into yield predictions for a range of scales (e.g., Baigorria et al., 2007b; Cabrera et al., 2009). Dynamic, process-oriented crop models have generally been developed and tested at a homogeneous plot scale to simulate as closely as possible crop growth and yield. However, applications related to climate variability are often at broader spatial scales where different drivers such as crop diseases and spatial heterogeneity of weather, soils, and management operate (Hansen and Jones, 2000). It is virtually impossible to measure all of the heterogeneous inputs required by crop models across a landscape, thus creating a gap between aggregated crop model outcomes and regional yield statistics.

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Signals like El Niño-Southern Oscillation (ENSO), which is a major driver of the annual variability in global climate (Neelin et al., 1998; Wang, 2005), have played an important role in forecasting crop yields in many regions of the world (e.g., Podestá et al., 2002; Fraisse et al., 2008). However, seasonal ENSO effects do not always coincide with important cropping seasons, especially during summers in the northern hemisphere (Hansen et al., 1998). In our study area, the Southeast (SE) United States, ENSO forecasts are currently used by crop specialists to provide agricultural outlooks to farmers (Fraisse et al., 2006; Hansen et al., 1998). However, cotton is not affected strongly by ENSO in this region as are other sensitive crops (Table 1) making it difficult to provide yield forecasts or management recommendations to farmer planting this economically important crop (Baigorria et al., 2008a).

Dynamic forecasts based on an Atmospheric Global Circulation Model (AGCM), driven by predicted sea surface temperatures, or on a coupled ocean atmospheric model (CGCM) may yield better results than categorical predictions based on ENSO alone (Davis et al., 1997; Stahle and Cleaveland, 1992). Previous research has used Global and Regional circulation model (GCM/RCM) forecasts to predict crop yields by either combining monthly bias-corrected GCM/RCM outputs with weather generators to produce daily weather data for input to crop models (i.e., Baigorria et al., 2007b, 2008b) or by directly using daily GCM/RCM outputs (Shin et al., 2006). However,

Abbreviations: AGCM, atmospheric global circulation model; CCA, canonical correlation analysis; CGCM, coupled ocean atmospheric model; ENSO , El Niño-Southern Oscillation; EOF, Empirical Orthogonal Function analysis; GCM/RCM, global and regional circulation model; PC, principal components.

Table 1. Measures of the El Niño-Southern Oscillation (ENSO)-based cotton yield forecast performance at a county level: Pearson's correlation (*R*) with statistical significance level, root mean square error (RMSE) as percentage of the mean crop yield in the specific county, and the percentage hit score (hits).

County, State	*R*	RMSE	Hits
		%	
Autauga, AL	–0.22ns†	26	26
Blount, AL	0.14ns	23	47
Burke, GA	0.18ns	22	45
Cherokee, AL	0.29ns	28	30
Clay, GA	–0.10ns	18	50
Colbert, AL	0.11ns	26	35
Colquitt, GA	0.24ns	17	50
Crisp, GA	0.42ns	20	35
Dooly, GA	0.17ns	28	30
Elmore, AL	0.18ns	22	35
Emanuel, GA	0.08ns	29	45
Escambia, AL	0.09ns	21	40
Etowah, AL	0.44ns	32	45
Fayette, AL	0.34ns	21	33
Houston, AL	0.38ns	24	45
Houston, GA	0.15ns	22	58
Jefferson, GA	0.05ns	23	30
Lauderdale, AL	0.26ns	25	40
Lawrence, AL	0.11ns	26	35
Lee, AL	0.41ns	20	44
Limestone, AL	0.14ns	27	40
Lowndes, AL	–0.12ns	23	40
Macon, AL	0.30ns	26	61
Macon, GA	0.18ns	25	40
Madison, AL	0.13ns	22	50
Monroe, AL	0.18ns	22	40
Pulaski, GA	0.24ns	26	35
Tift, GA	0.12ns	19	40
Tuscaloosa, AL	0.44ns	18	58
Washington, GA	–0.21ns	24	33
Wilcox, GA	0.26ns	22	50

† ns = not significant.

timing of precipitation or extreme events may greatly affect simulated outcomes (e.g., Baigorria et al., 2007b; Wheeler et al., 2000).

One alternative to link numerical climate and dynamic crop models is to use the global seasonal climate forecasts to develop empirical relationships for predicting crop yields at regional scales. Challinor et al. (2003) used seasonal climate forecasts to predict peanut (*Arachis hypogaea* L.) yield in India. When their climate forecasts captured the leading modes associated with peanut yields, they could be used directly for crop yield prediction. Baigorria et al. (2008a) used this concept in measuring the potential predictability of cotton yields in the SE United States, using wind patterns derived from the National Centers for Environmental Prediction and National Center for Atmospheric Research (NCEP–NCAR) Climate Data Assimilation System (CDAS) Reanalysis data (Kalnay et al., 1996), and forecasts from the ECHAM 3.5 GCM using prescribed sea surface temperatures. Their study demonstrated that certain wind patterns in the upper troposphere, together with surface temperatures, could be used to predict cotton yields in the region. However, the lack of climate model skill in forecasting winds at 200 hPa prevented its effectiveness and implementation.

Cotton harvesting in Alabama and Georgia typically runs from late September through November. For cotton planted in April (15–30 April), farmers harvest from late September to late October. If cotton experiences drought conditions in the summer, farmers tend to wait for rain to let the cotton plants complete their growth cycle. In these cases, harvesting is delayed until late November (J. Paz, personal communication, 2009). Consequently, crop forecasts made before planting have a lead time of 6 mo or more.

In addition to rain, temperature is important during the reproductive phase of cotton. Day and night temperatures higher than 20 and 30°C, respectively, increase abortion of reproductive structures (Reddy et al., 1991, 1992); whereas high humidity during flowering and fiber formation causes a higher incidence of fungal diseases, such as hardlock of cotton, which is mainly associated with the fungus *Fusarium verticillioides* (Mailhot et al., 2007; Marois et al., 2005), and boll rot, caused by fungal and bacterial pathogens (Jost et al., 2005). The effect of high temperatures on pollen germination and pollen tube growth depends mainly on the cotton cultivar. The optimum mean temperature for pollen germination and pollen tube growth is approximately 31°C (ranging from 28–35°C) and 28°C (ranging from 26–33°C), respectively (Kakani et al., 2005). Surpassing these thresholds causes lower cotton yield due to a decreased number of bolls and to an increased incidence of pests and diseases (Mailhot et al., 2007). Hence, high temperatures southward toward Florida limit cotton production in this region.

In the United States, cotton is cultivated as an annual crop with a growing season longer than 6 mo. For this research, the cropping season length was split into the first 3-mo vegetative growth period (April–June), when the plant develops its canopy and root structure, and a second 3-mo reproductive period (July–September).

In this paper, we examine the possibility of using the CGCM seasonal forecasts, Reanalysis data, and observed rainfall to forecast cotton yields at the county level in Alabama and Georgia (between 35°18′ N, 88°30′ W and 29°00′ N, 80°48′ W). The overall objective of our research was to develop and evaluate a seasonal climate-based cotton yield forecast using a CGCM that would provide better medium- and short-range forecasts than the current ENSO-based forecasts in the SE United States. Questions addressed are: (i) is it possible to improve cotton yield forecast skill at a county scale by using statistical downscaling of CGCM outputs, relative to skill based on ENSO phase, and (ii) is it possible to combine different sources of observed and forecasted climatic variables of different temporal and spatial scales for forecasting cotton crop yields.

The short-range near-term cotton yield forecast in this study was based on the statistical CCA method using Reanalysis data available at the end of September each year, when cotton harvest begins in the region. The medium-range cotton yield forecasts was based on the outputs from the CGCM forecasts made in June.

DATA

Cotton Yield Data

Cotton yield data for 1970 to 2006 from 57 counties in Alabama and Georgia with significant areas devoted to cotton production (1,500–22,000 ha), were obtained from the National Agricultural Statistics Service (http://www.nass.usda.gov; verified 30 Nov. 2009) of the USDA (Fig. 1). According to USDA-NASS (2009), 6% of the 154,818 ha of croplands in

Alabama, and 31% of the 403,239 ha of croplands in Georgia were planted with cotton in 2007. However, agricultural censuses are not performed every year, and irrigated areas have changed without a well-defined trend during the 37-yr period used in this study. Therefore, a drawback in the time series yield data is that they do not distinguish between irrigated and rainfed areas, and there is not a clear trend from the censuses that permits any type of interpolation. This lack of information is a source of uncertainty, since irrigation makes crops less sensitive to the seasonal variability of rainfall. According to the same census, on average, irrigated areas in Georgia produced 64% more cotton yields in 2007 than rainfed areas.

Climate Data

Three climate data sets were used in this study: (i) Rainfall totals for April–May–June for the period 1970 to 2006 from the NOAA/NWS/National Climate Data Center (http://www.ncdc.noaa.gov/oa/ncdc.html; verified 30 Nov. 2009). A total of 62 weather stations in the SE United States were used in this study (Fig. 1). (ii) The July–August–September averaged 2-m mean temperature for the period 1970 to 2006 from reanalysis data (http://www.cdc.noaa.gov/data/gridded/data.ncep.reanalysis.html; verified 30 Nov. 2009) (Kalnay et al., 1996). The horizontal resolution of these data is 2.5 degrees. (iii) The July–August–September averaged 2-m mean temperature from the NCEP Climate Forecast System (http://cfs.ncep.noaa.gov; verified 30 Nov. 2009) (CFS; Saha et al., 2006). The CFS forecasts have a horizontal resolution of approximately 2.5 degrees and cover the period from 1981 to 2006.

The 2-m mean temperatures from July to September were for the geographical domain between 35° North latitude, 90° West longitude, and 30° North latitude, 80° West longitude. The period from 1970 through 2006 was used in this study to avoid long-term trends in rainfall detected in southeastern Alabama and part of southwestern Georgia during the convective rainy season (Baigorria et al., 2007a).

Reanalysis data (Kalnay et al., 1996) refer to a gridded assimilated atmospheric dataset created by using data from observation network and the state-of-the-art models to come up with the best analysis (vertical and horizontal consistency of variable fields) of the historical record across the atmosphere at global scale. The process of re-analyzing the observed data begins by producing a 6-h forecast. Then observations from aircrafts, satellites, weather stations, sondes, and others are injected to correct the 6-h forecast (3DVAR) to finally come up with the Reanalysis data. Using as initial conditions the previously obtained 6-h Reanalysis data, another 6-h forecast is produced and another cycle is then performed.

CFS is the NCEP's fully coupled ocean-land-atmosphere dynamic seasonal prediction system, operational since August 2004. The model includes atmosphere-ocean coupling spans almost all the globe, and is a fully coupled modeling system with no flux corrections (see Saha et al., 2006). We used an equal weighted mean of 15 ensemble members for 1981

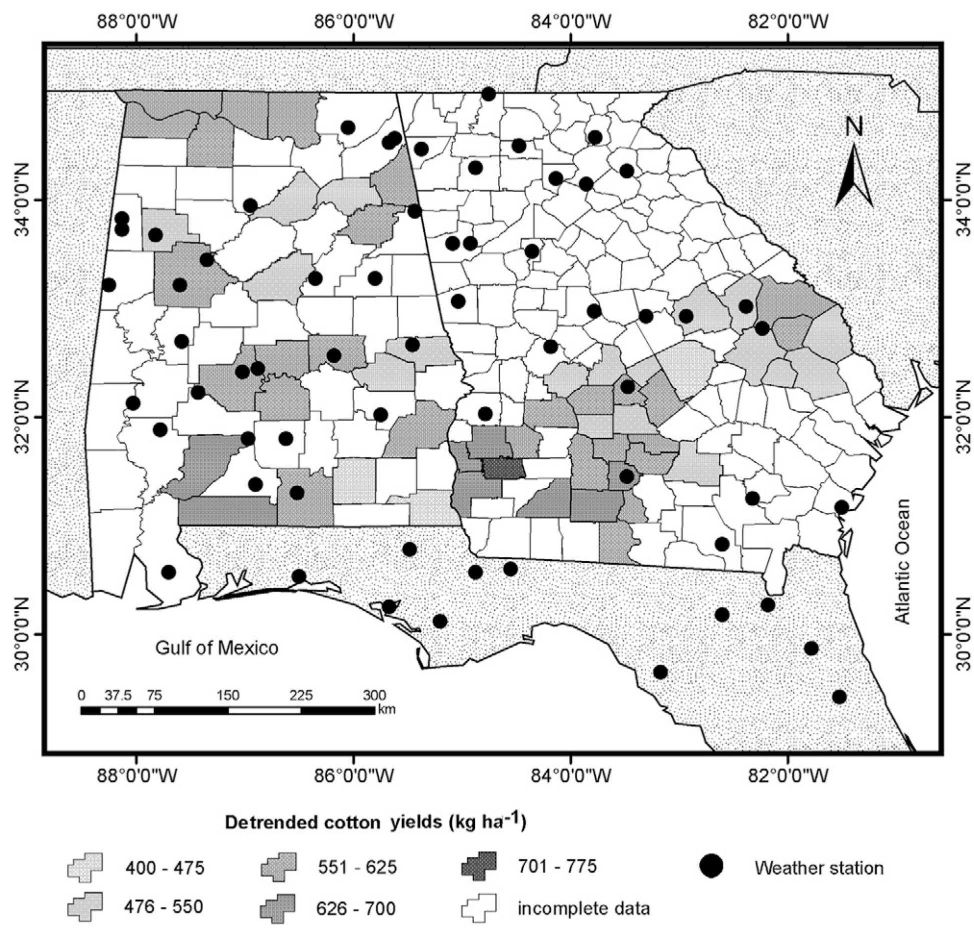

Fig. 1. Detrended cotton yields and weather station network map.

through 2006 from the CFS retrospective forecasts. An ensembled is a set of deterministic realizations of a model that collectively represent a probability distribution. Each ensemble member (realization) has equal probability of occurrence. Ensemble methods are used in stochastic models when the underlying probability distributions cannot be represented by analytical expressions. The CFS ensemble mean included ensemble members 1 to 5 initialized from the 9th to 13th of June each year, members 6 to 10 from the 19th to 23rd of June, members 11 to 12 from the 29th to 30th of June, and members 13 to 15, from the first to third of July.

MATERIALS AND METHODS

Postprocessing the Historical Records of Cotton Yields

The historical annual cotton yields from the 57 counties were detrended, and the results were geospatially aggregated using principal components (PC). The resulting time series was the target to be forecasted (the predictand).

Detrending Technology from Crop Yield Statistics

Many anthropogenic factors have cumulative influences on crop yield trends. These technological achievements include use of improved crop varieties, development, and application of improved irrigation systems, mechanization, and increases in soil fertility. Analysis of cotton yield time series data must first account for such trends. Crop yields have increased in a nonlinear fashion over the analyzed period of time in the study area. There is no theoretical basis for assuming any particular parametric functional form (e.g., linear). Instead, it is more appropriate to detrend the time series using a filter that takes into account a variable that is both slowly increasing and affected by random noise. It was assumed that the influence of inter-annual climate variability on cotton yield generally occurs at a higher frequency than nonclimatic influences, which are assumed to be only positive (agricultural technologies that do not work are discarded almost immediately). A low-pass spectral filter (Press et al., 2007) was used to detrend the time series data (Baigorria et al., 2008a; Fraisse et al., 2008; Martinez et al., 2009). This filter removed the linear trend and applied a Fourier transform filter to the residuals to generate a low-frequency yield trend. Finally, the yield trend was removed from the crop yield observations to obtain the high-frequency detrended data for comparing with the interannual climate variability. Since the choice of the length of the low frequency period was subjective, the following considerations were taking into account: (a) the length was selected to be the minimum number of years, greater than or equal to 10 yr, to avoid ENSO-related climate variability, and (b) the trend considered only positive values during the evaluated 37-yr period. In this way, the removal of annual fluctuations in yield associated with climate variability was avoided.

Geospatial Aggregation of Detrended Crop Yields

The two-dimensional patterns of the detrended crop yields were created by using Empirical Orthogonal Function analysis (EOF). Afterward, the detrended crop yields were projected onto the first EOF to obtain the time series of principal component one ($PC1_c$). Principal components are independent variables created through orthonormal linear transformations of a multivariate data set that successively maximizes the residual variance that remains after higher-order PCs are removed. The transformation consists of reducing the correlation matrix to a diagonal matrix (composed of eigenvalues) by pre- and postmultiplying it with a particular orthonormal matrix containing columns called eigenvectors which are orthogonal among themselves (Jackson, 2003; Jolliffe, 2004). For this analysis, a correlation matrix was used rather than a covariance matrix to avoid the tendency for the first few eigenvectors to give the highest weights to locations having the largest variances (Jackson, 2003; Jolliffe, 2004; Wilks, 2006).

The first PC ($PC1_c$) represents the geospatially aggregated detrended cotton yields from the 57 counties. $PC1_c$ is a time series with 37 weighted values corresponding to the years 1970 through 2006 and represents the interannual variability of the geospatially aggregated detrended cotton yields. Because the relationship between each county's detrended cotton yield and the $PC1_c$ was known, the final step after forecasting $PC1_c$ (the predictand) was to disaggregate forecasts to county level cotton yield forecasts using the reverse process.

Detecting the Effect of Regional Two-Meter Mean Air Temperature and Rainfall on Cotton Yields

Figure 2 shows temperatures in July when most cotton is flowering over the SE United States. Figure 2a shows the Reanalysis data climatology of 2-m mean temperatures in the SE United States, and Fig. 2b shows the 2-m mean July temperature anomalies averaged across the five highest yielding years of cotton (1982, 1984, 1985, 1991, and 1994). During these years, temperatures were lower than average. For the 5 yr during which cotton yield anomalies were lowest (1977, 1980, 1986, 2000, and 2002), temperatures were higher than average (Fig. 2c). During these years, some areas of the region had higher July temperature means than the threshold of reproductive structure abortion.

The first principal component ($PC1_T$) of July–August–September 2-m mean temperature was calculated based on the correlation matrices to summarize the spatial and temporal information (see Geospatial Aggregation of Detrended Crop Yields). In preliminary exploratory studies, it was found that July–August–September 2-m mean temperature did provide some ability to predict cotton yields, since crop conditions during flowering affect final yields. However, further analyses (not shown in this paper) demonstrated that the CFS had a low skill in forecasting 3-mo lead-time of 2-m mean temperatures during the cropping season (most of the summer) in the region. This prevented the use of this variable directly as predictor of the detrended cotton yields.

Rainfall during vegetative growth, from April to June, was found to be correlated with cotton yields, as unstressed conditions during vegetative growth produce vigorous canopies, which are important for flowering and lint development. However, CFS had a low skill in forecasting 1-mo lead-time rainfall in the region during summertime; therefore, region-wide total April–May–June observed rainfall at a weather station level was incorporated as a predictor together with July–August–September 2-m mean temperatures to increase the predictability of cotton yields harvested in late September and November.

Total observed rainfall during vegetative growth from April to June was averaged across all 62 weather stations ($\overline{R}_{AMJ}$). Using iterative search, a minimum threshold (τ) of $\overline{R}_{AMJ}$ was established after comparing time series of $PC1_c$ (see Geospatial Aggregation of Detrended Crop Yields) and R_{AMJ}. All values below this threshold produced negative residual yields.

To incorporate the dichotomous rainfall effects (above or below the established threshold) into 2-m mean temperature $PC1_T$, an index was developed. This correction index (D_k) was calculated as the ratio between the amount of rainfall excess or deficit compared to the threshold (τ) and τ:

$$D_k = \frac{\left(\overline{R}_{AMJ} - \tau\right)}{\tau} \qquad [1]$$

$PC1_T$'s temporal scores during years (y) with $\overline{R}_{AMJ}$ less than τ mm ($D_k < 0$) received a penalty proportional to the $PC1_T$'s temporal score of the driest year (y^*) before the evaluated year.

$$\begin{cases} D_{k_y} \geq 0; & PC1_{T-R,y} = PC1_{T,y} \\ D_{k_y} < 0; & PC1_{T-R,y} = PC1_{T,y} + \left(F \times PC1_{T,y^*}\right) \end{cases} \qquad [2]$$

where $PC1_{T\text{-}R}$ is the rainfall-based modified 2-m mean temperature. The proportionality factors (F) were recalculated only during years when $\overline{R}_{AMJ}$ was under τ (mm). Thus, the first calculation of F was performed for 1977, since the previous year's records had $\overline{R}_{AMJ}$ over τ. F was estimated by an iterative method. Iterations were performed to minimize the mean square error (MSE) between $\overline{R}_{AMJ}$ the spatially aggregated detrended cotton yield $PC1_c$ and their corresponding $PC1_T$ temporal scores. F was calculated using the period before the evaluated year to assure independency between calibration and validation datasets, thus avoiding overestimations on the forecast performance. Two different sets of F were calculated: one when $PC1_T$ was calculated using Reanalysis data and the other when $PC1_T$ was calculated using CFS's forecasts. Each set of F were used to calculate their respective $PC1_{T\text{-}R}$ which were used later as a predictor in the short-range, near-term, and the medium-rage forecasts.

Cotton Yield Forecasts

Short-Range Near-Term Forecasts Based on the Reanalysis Data

The detrended cotton yield $PC1_c$ was forecasted using the Canonical Correlation Analysis (CCA) regression-based model. The predictor was the rainfall-based modified 2-m mean temperature $PC1_{T\text{-}R}$ for July–September obtained from Reanalysis data. Performance of the CCA regression-based model was assessed using two validation methods: the leave-one-out cross-validation (Barnston and van den Dool, 1993; Efron and Tibshirani, 1993; Shao, 1993) and the retroactive validation (Landman et al., 2001; Wilks, 2006). For leave-one-out cross-validation, the training period used was from 1970 to 2006. For retroactive validation, the initial training period was from 1970 to 1986, increasing 1 yr at a time for each new independent forecast. For comparison purposes, only the independent yearly cotton yield forecasts from 1987 to 2006 were used.

The Pearson's correlation, the root mean square error (RMSE) and the hit score were used for validation. Hit score is defined as the probability of forecasting the correct tercile (above-normal, normal, and below-normal; Wilks, 2006). As an overall measure of predictability, the Goodness-of-Fit Index (GFI) was calculated as the all-county-average Pearson's correlation.

Medium-Range Forecasts Based on the Climate Forecast System Model Outputs

The detrended cotton yield $PC1_c$ was forecasted using a CCA regression-based model. The predictor $PC1_{T\text{-}R}$ was obtained from CFS's forecasts. The forecast performance of the CCA regression-based model was assessed based on three validation methods: (i) the leave-one-out cross-validation, (ii) the retroactive validation, and (iii) the coral-reef validation.[1]

The first two validation methods use only one type of input information at a time (Mason and Tippett, 2008). For instance, the CCA regression-based model is calibrated using CFS forecasts for a given training period. After that, the model

[1] Name given to the method from its similarity to the hard coral reef's accumulated annual growth.

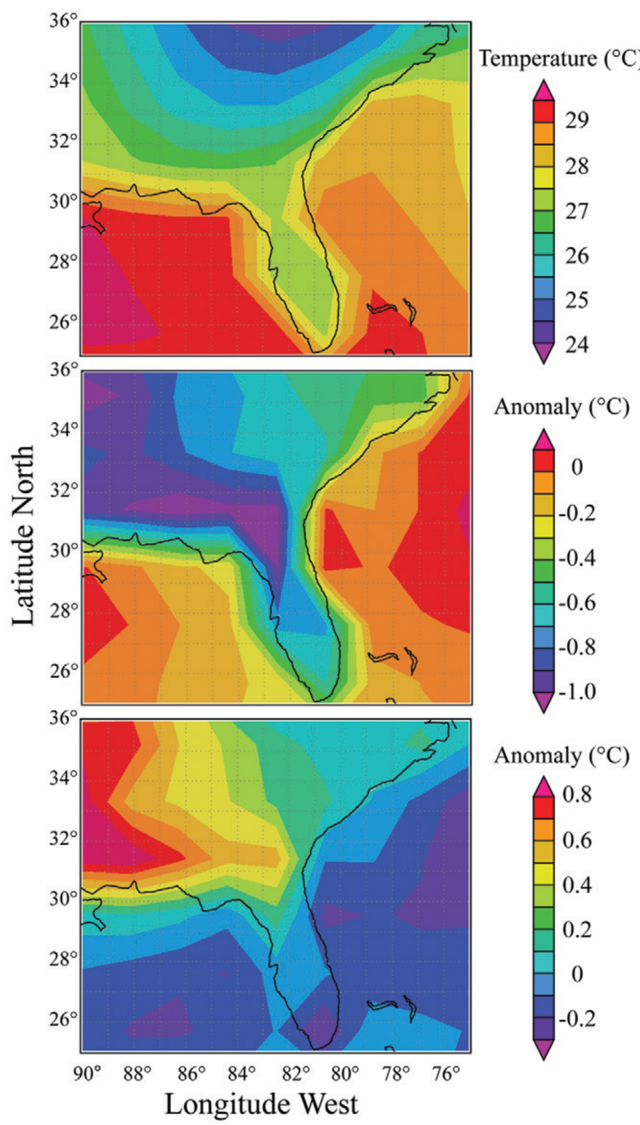

Fig. 2. Temperature regime in the Southeast United States in July: (a) climatology and anomalies during the (b) five highest cotton yield years, and (c) five lowest cotton yield years.

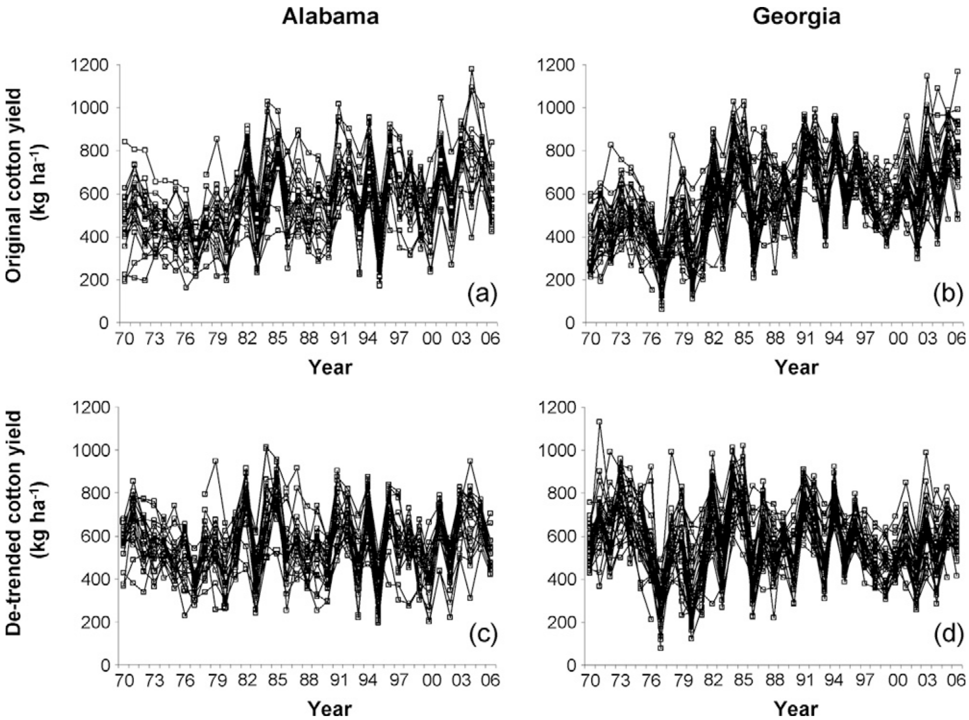

Fig. 3. Detrended cotton yields for all counties in Alabama and Georgia: (a) Alabama's original cotton yield time series, (b) Georgia's original cotton yield time series, (c) Alabama's detrended cotton yield time series, (d) Georgia's detrended cotton yield time series.

uses the same type of input (CFS forecasts) to forecast target years that are not included in the training period.

A new validation method, referred to as coral-reef validation, is similar to retroactive validation but it uses the Reanalysis data for calibration and the CFS forecasts as inputs for the realizations. This method is based on the use of a seasonal climate forecast as an estimate of a future observation; thus, forecasts belong to the same population as observations, and therefore they can be combined.

The coral reef method begins by selecting the training period for model calibration, which is a continuous subset taken from the total time series length of yearly Reanalysis data. The training period always begins with the first year of the time series. After calibrating the CCA regression-based model, a CFS seasonal climate forecast corresponding to the year following the training period is used as input to forecast cotton yields for that specific year. For every validation cycle, the training period increases 1 yr and the resulting model is used to forecast cotton for the season during which the CFS climate forecast is available. The last cycle is reached when the training period length is equal to the time series length minus 1 yr, 36 yr in our study.

Pearson's correlation, with its statistical significance level, GFI, RMSE, and probability of forecasting the correct tercile were also computed for evaluating forecast skill. For leave-one-out cross-validation, the training period used was from 1970 to 2006. For both retroactive validation and coral-reef validation, the initial training period was from 1970 to 1986, increasing 1 yr at a time for each new forecast cycle. As in the previous section, for comparison purposes only forecasts of yearly cotton yields from 1987 to 2006 were used.

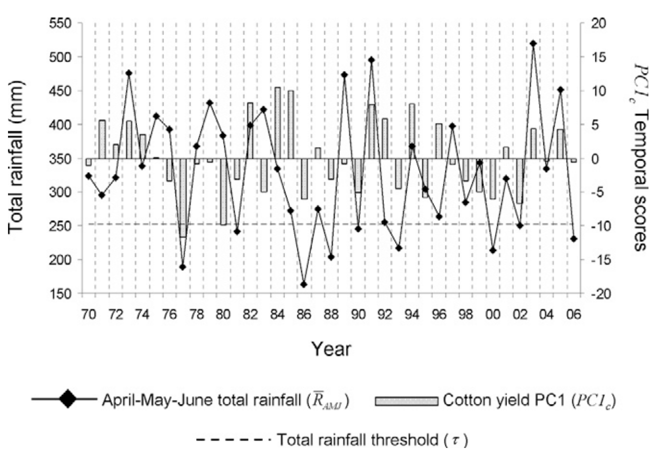

Fig. 4. Time series of (a) detrended cotton yield $PC1_c$ and (b) the total all-weather-station-average rainfall during cotton's vegetative growth period (April–May–June).

The forecasts were performed only in the counties where statistical significance ($p < 0.05$) was found during the short-range near-term forecast analysis using any of the previous methods.

RESULTS AND DISCUSSION

Postprocessing Historical Records of Cotton Yields

Figure 3 shows the results of the detrending process for all counties in each state. The original crop yield time series (Fig. 3a and 3b) showed a tendency toward lower values during the 70s and higher values during and after the 90s. After detrending the time series (Fig. 3c and 3d), this tendency was removed, although year by year variability remained as expected. Spatial distribution of the mean detrended cotton yields for all counties are shown in Fig. 1.

Figure 4 shows the first principal component ($PC1_c$) of the detrended cotton yield, which represents the geospatially aggregated cotton yield from the 57 counties. This $PC1_c$ alone explained 63% of the variance in the data. $PC1_c$ time series was the variable that was predicted (predictant) by the short-range, near-term, and the medium-range forecasts.

Effects of Regional Two-Meter Mean Air Temperature and Rainfall on Cotton Yields

Figure 4 shows the all-weather-station-average rainfall totals for April–May–June ($\overline{R}_{AMJ}$) in addition to $PC1_c$. It can be seen in the figure that there was no apparent relationship between $\overline{R}_{AMJ}$ and $PC1_c$; correlation between these variables was only 0.38. However, all $PC1_c$ yearly temporal scores were negative when $\overline{R}_{AMJ}$ was < 250 mm (the opposite was not always true). Thus, the threshold τ was set to 250 mm.

Figure 5a shows the D_k time series, while Fig. 5b compares $PC1_c$ (inverse scale) vs. (i) 2-m mean temperature PC1 ($PC1_T$)

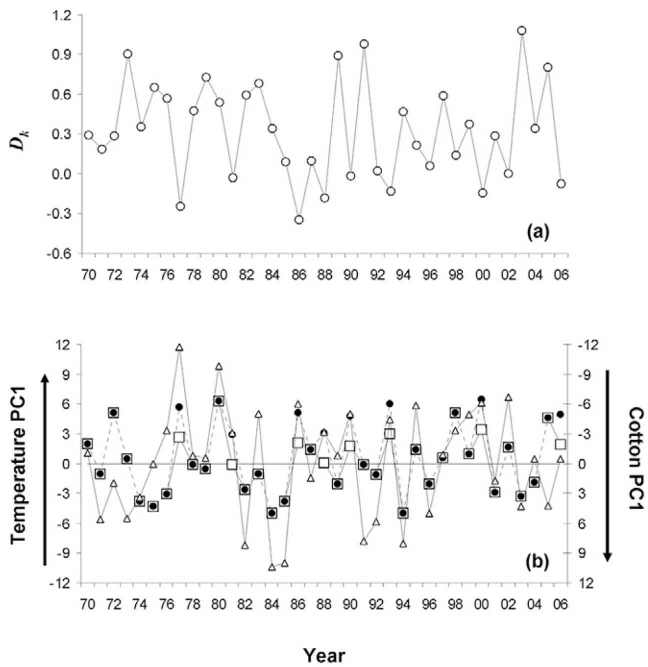

Fig. 5. Time series of: (a) D_k index (o), and (b) detrended cotton yield PC1$_c$ (Δ), 2-m mean temperature PC (PC1$_T$, open square), and rainfall-corrected 2-m mean temperature PC (PC1$_{T-R}$, closed circle).

and, (ii) 2-m mean temperature PC1 incorporating the rainfall effect (PC1$_{T-R}$). Years showing an overlap between the open square and the solid circle are years when the rainfall threshold of 250 mm was not surpassed ($D_k \geq 0$). In the remaining years, the difference between both symbols represents the correction due to water stress during vegetative growth of the crop. While performing the iterative process to estimate the proportionality factor (F) using Reanalysis data, F values ranged from 2.7 to 1.7; whereas using CFS forecasts F values ranged from 2.0 to –2.1. Variability of the F values decreased as more years were added to the calculations. To perform new short-range near-term forecasts using Reanalysis data, the F value must be set to 1.7; whereas for new medium-range forecasts using CFS forecasts, the F value must be set to –1.0. These values are recalculated every time a new year with < 250 mm $\overline{R}_{AMJ}$ appears in new years where forecasts are computed.

Cotton Yield Forecasts

Short-Range, Near-Term Forecast Based on the Reanalysis Data

The PC1$_{T-R}$ significantly ($p < 0.05$) forecasted cotton yields in 31 out of the 57 counties that were originally selected (Fig. 6). The efficiency of the model at forecasting cotton yield in the SE United States was greater than that of the ENSO-based categorical forecast (Tables 1, 2, and 3). Retroactive validation showed a statistically significant increase of 26% in comparison to the leave-one-out cross-validation. All 31 statistically significant forecasted counties produced by the leave-one-out cross-validation method matched those of the retroactive validation. The accuracy of cotton yield forecasts for these 31 counties demonstrates a potential level of skill of our methodology to forecast cotton yields in Alabama and Georgia under a perfect seasonal climate forecast (CFS forecasts equal to Reanalysis data).

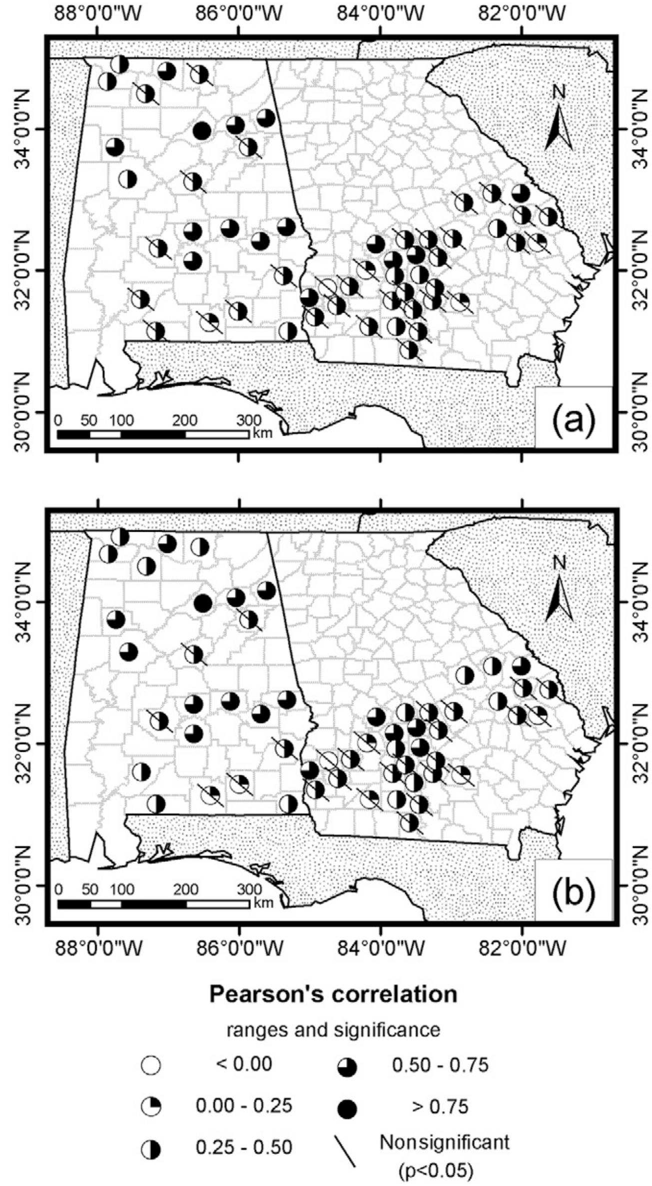

Fig. 6. Short-range, near-term cotton yield forecasts using (a) leave-one-out cross-validation, and (b) retroactive validation for the 1987–2006 time period.

Leave-one-out cross-validation and retroactive validation produced GFIs of 0.50 and 0.53, respectively. Root mean square errors among counties ranged between 15 and 30% of mean county yields for cross-validation and between 16 and 30% for retroactive validation. The percentage of hit scores ranged from 35 to 65% and 40 to 73% for cross-validation and retroactive validation, respectively. Compared to ENSO-based cotton yield forecasts (GFI = 0.17, RMSE ranging between 17 and 32%, and hit scores ranging from 26 to 61%) these are improved results.

Medium-Range Forecasts Based on the CFS Model Outputs

Leave-one-out cross-validation produced a GFI of 0.23 and retroactive validation gave a result of 0.23, whereas coral-reef validation produced a value of 0.43. Colquitt County in Georgia (Table 2) was the only location where both cross-

Table 2. Measures of the cotton yield forecast performance at a county level for Georgia: Pearson's correlation (*R*) with statistical significance level, root mean square error (RMSE) as percentage of the mean crop yield in the specific county, and the percentage hit score (hits).

	Short-range near-term forecasts						Medium-range forecasts								
	Cross-validation			Retroactive validation			Cross-validation			Retroactive validation			Coral-reef validation		
County	*R*	RMSE	Hits	*R*	RMSE	Hits	*R*	RMSE	Hits	*R*	RMSE	Hits	*R*	RMSE	Hits
		%			%			%			%			%	
Burke	0.55*	20	60	0.60**	22	55	0.06ns†	23	60	0.08ns	24	55	0.30ns	27	50
Clay	0.53*	17	50	0.53*	19	44	0.33ns	17	50	0.39ns	17	67	0.47*	18	56
Colquitt	0.49*	15	50	0.50*	16	50	0.54*	15	70	0.55*	16	50	0.64**	13	55
Crisp	0.47*	20	45	0.48*	21	50	0.28ns	20	35	0.33ns	20	40	0.45*	20	60
Dooly	0.57**	25	50	0.60**	25	50	0.28ns	28	45	0.31ns	28	35	0.49*	27	45
Emanuel	0.46*	26	45	0.48*	26	50	0.07ns	29	55	0.20ns	30	50	0.25ns	30	55
Houston	0.45ns	22	63	0.48*	23	63	0.19ns	22	63	0.21ns	23	53	0.34ns	25	53
Jefferson	0.43ns	22	50	0.50*	24	40	0.02ns	23	45	0.12ns	24	45	0.29ns	28	35
Macon	0.57**	21	60	0.61**	22	65	0.44ns	23	50	0.41ns	23	45	0.64**	20	50
Pulaski	0.59**	22	65	0.60**	23	60	0.15ns	27	30	0.27ns	27	45	0.35ns	28	40
Tift	0.40ns	15	35	0.47*	16	50	0.22ns	16	40	0.28ns	19	35	0.48*	16	50
Washington	0.46ns	22	61	0.48*	25	61	0.16ns	22	33	0.27ns	23	50	0.32ns	26	44
Wilcox	0.48*	19	55	0.51*	19	50	0.22ns	21	55	0.26ns	21	50	0.38ns	21	55

* Significant at the 0.05 probability level.

** Significant at the 0.01 probability level.

† ns = not significant.

validation and retroactive validation methods produced significant forecasts.

The coral-reef validation, combined with region-wide rainfall from weather stations and 2-m mean temperatures from Reanalysis data and CFS forecasts, significantly forecasted cotton yields in 48% of the counties where the short-range near-term forecasts performed adequately (Fig. 7). For those counties where there were significant forecast performances, the GFI was 0.51, Pearson's correlation ranged from 0.63 to 0.45, the RMSE ranged between 13 and 31%, and the percentage of hit scores ranged between 35 and 61% (Tables 2 and 3).

Cotton Yield Forecasts: Potential and Limitations

The lack of predictability in most of the studied counties using both short-range near-term and medium-range forecasts was mainly due to the following:

(i) Missing values in the agricultural statistics (this is apparent from the fact that only 57 out of the 211 counties initially selected from Alabama, Florida, and Georgia were used in the final research).

(ii) Spatial variability in soils and crop management practices within the same county (i.e., irrigation vs. rainfed fields, planting dates, cultivars). In general terms, more counties were significantly predicted in

Table 3. Measures of the cotton yield forecast performance at a county level for Alabama: Pearson's correlation (*R*) with statistical significance level, root mean square error (RMSE) as percentage of the mean crop yield in the specific county, and percentage hit score (hits).

	Short-range near-term forecasts						Medium-range forecasts								
	Cross-validation			Retroactive validation			Cross-validation			Retroactive validation			Coral-reef validation		
County	*R*	RMSE	Hits	*R*	RMSE	Hits	*R*	RMSE	Hits	*R*	RMSE	Hits	*R*	RMSE	Hits
		%			%			%			%			%	
Autauga	0.56*	22	53	0.58**	21	53	0.30ns†	25	32	0.31ns	25	26	0.49*	23	47
Blount	0.77**	15	60	0.76**	16	73	0.17ns	21	67	0.14ns	21	60	0.54*	19	53
Cherokee	0.53*	25	45	0.55*	25	45	0.11ns	29	40	0.12ns	29	30	0.36ns	28	40
Colbert	0.45*	23	45	0.48*	23	45	0.21ns	26	40	0.04ns	28	30	0.40ns	24	45
Elmore	0.50*	20	45	0.52*	20	45	0.29ns	22	55	0.26ns	23	50	0.44ns	22	40
Escambia	0.41ns	18	45	0.45*	18	50	0.06ns	21	25	0.03ns	23	35	0.20ns	21	35
Etowah	0.51*	30	65	0.53*	30	55	0.23ns	34	35	0.16ns	35	35	0.45*	31	35
Fayette	0.56*	18	60	0.57*	19	67	–0.04ns	23	27	–0.01ns	24	47	0.34ns	22	40
Houston	0.45*	22	50	0.47*	22	50	0.30ns	23	60	0.39ns	24	50	0.45*	22	55
Lauderdale	0.47*	23	50	0.49*	23	50	0.15ns	26	40	–0.06ns	28	35	0.41ns	24	45
Lawrence	0.44ns	23	55	0.47*	23	55	0.25ns	25	35	0.11ns	26	35	0.46*	23	35
Lee	0.57*	18	56	0.57*	18	61	0.34ns	22	56	0.15ns	24	50	0.51*	20	56
Limestone	0.54*	22	50	0.56**	22	60	0.34ns	25	30	0.24ns	26	25	0.56*	22	55
Lowndes	0.54*	18	53	0.55*	18	60	0.29ns	21	40	0.28ns	23	33	0.44ns	20	47
Macon	0.50*	24	61	0.52*	23	72	0.31ns	27	50	0.23ns	29	44	0.50*	24	61
Madison	0.43ns	21	60	0.47*	24	40	0.26ns	21	50	0.28ns	21	50	0.39ns	23	35
Monroe	0.44ns	20	60	0.46*	20	60	0.13ns	22	40	0.42ns	23	60	0.28ns	22	50
Tuscaloosa	0.49*	17	42	0.51*	18	42	0.42ns	18	32	0.35ns	19	37	0.57*	17	37

* Significant at the 0.05 probability level.

** Significant at the 0.01 probability level.

† ns = not significant.

Alabama than in Georgia. Taking into account that currently only 6% of the cotton in Alabama is under irrigation compared to 31% in Georgia, we speculate that irrigation management in Georgia is an important factor in limiting the forecast success. Furthermore, there was a weak tendency for higher predictability in counties with low average yields, which likely corresponds to areas with low soil fertility and/or crop management.

(iii) The low resolution of the available Reanalysis data and CFS seasonal climate information (one grid cell size equivalent to 66,850 km^2); and

(iv) The low skills of the seasonal climate forecasts in the studied region produced by the CFS model. The short-range near-term forecast used global scale observed assimilated data. Therefore, cotton yield forecasts using these data represents an upper limit for the statistical methods used in this paper. Potentially, improvements in the CFS model can increase the lead time for forecasting cotton yields, possibly even before planting. Increasing predictability skills of the CFS would provide more climatic variables that are known to affect cotton yields, such as incoming solar radiation and humidity, for use as predictors in new statistical relationships.

CONCLUSIONS

Cotton yields in 15 counties of Alabama and Georgia were successfully forecasted 3 mo before initiation of the harvest season, and the cotton yields in 31 counties were successfully forecasted just before the harvest season.

Using as a criterion the number of counties significantly forecasted, the coral-reef validation, which combined observed and forecasted data, produced better results than the standard leave-one-out cross-validation and the retroactive validation using only observed or forecasted data. The combined use of observed rainfall at weather station level, Reanalysis data and CFS forecasts improved the ability to forecast cotton yields in the SE United States compared to the use of ENSO-based forecast. The improvement can be measured by the increment of the GFI in 0.30. Unfortunately, despite the improvement in the forecasts, the number of counties forecasted with a significant level of $p < 0.05$ are not enough for considering a regional operational application of the methods.

Improvements in the skills and resolution of the CFS model and the Reanalysis data will potentially lead to improvements in the predictions of cotton yields in the region. Improvements in the annual agricultural statistics (i.e., missing values and the percentage of rainfed and irrigated cotton fields per county) will also lead to improvements in the predictions, since irrigation makes crops less susceptible to water stress. Usefulness of the short-range near-term forecast may be arguable, but as CGCM forecast skills increase, the potential to forecast cotton yield earlier in the growing season or even before planting also increases.

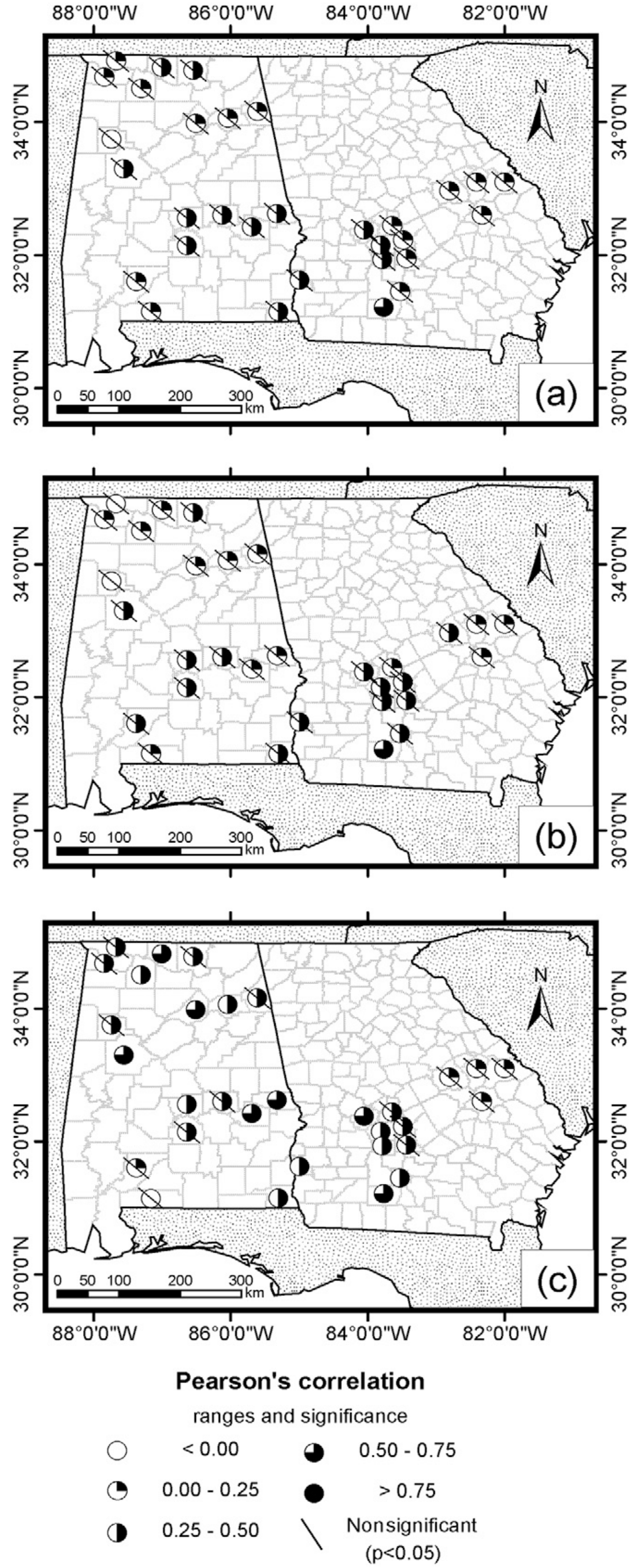

Fig. 7. Medium-range cotton yield forecasts for the counties that showed significant prediction during the short-range, near-term forecasts using (a) leave-one-out cross-validation, (b) retroactive validation, and (c) coral-reef validation. Period 1987–2006.

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