CLIMATE SCENARIOS FOR THE SOUTHEASTERN U.S. BASED ON GCM AND REGIONAL MODEL SIMULATIONS

L. O. MEARNS [1], F. GIORGI [2], L. McDANIEL [1] and C. SHIELDS [1]

[1] *National Center for Atmospheric Research,⋆ Boulder, Colorado, U.S.A.*
[2] *Abdus Salam International Centre for Theoretical Physics, Trieste, Italy*

Abstract. We analyze the control runs and 2 × CO_2 projections (5-year lengths) of the CSIRO Mk 2 GCM and the RegCM2 regional climate model, which was nested in the CSIRO GCM, over the Southeastern U.S.; and we present the development of climate scenarios for use in an integrated assessment of agriculture. The RegCM exhibits smaller biases in both maximum and minimum temperature compared to the CSIRO. Domain average precipitation biases are generally negative and relatively small in winter, spring, and fall, but both models produce large positive biases in summer, that of the RegCM being the larger. Spatial pattern correlations of the model control runs and observations show that the RegCM reproduces better than the CSIRO the spatial patterns of precipitation, minimum and maximum temperature in all seasons. Under climate change conditions, the most salient feature from the point of view of scenarios for agriculture is the large decreases in summer precipitation, about 20% in the CSIRO and 30% in the RegCM. Increases in spring precipitation are found in both models, about 35% in the CSIRO and 25% in the RegCM. Precipitation decreases of about 20% dominate in winter in the CSIRO, while a more complex pattern of increases and decreases is exhibited by the regional model. Temperature increases by 3 to 5 °C in the CSIRO, the higher values dominating in winter and spring. In the RegCM, temperature increases are much more spatially and temporally variable, ranging from 1 to 7 °C across all months and grids. In summer large increases (up to 7 °C) in maximum temperature are found in the northeastern part of the domain where maximum drying occurs.

1. Introduction

Climate change experiments with regional climate models (RCMs) nested in coarser resolution general circulation models (GCMs) have become common particularly over the past half decade (Giorgi et al., 2001), and are now being used to form climate scenarios for input to impact models (Mearns et al., 2001). This development has been welcomed by the climate impacts community since dissatisfaction with the coarse spatial scale of general circulation model (GCM) simulations used to form climate scenarios for impacts use has been widely expressed (Gates, 1985; Cohen, 1990; Carter et al., 1994). It is perceived that there is a serious mismatch in scale between that of the global climate models (100s of km) and the scale of concern for most regional impact assessments (at least an order of magnitude finer). For example, crop models operate at spatial resolutions of a single plant to a

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few meters to hectares. Fine scale variations in climate not simulated by GCMs are potentially important to the scale of concern for various resources such as agriculture.

In this paper we present climate model simulations that were expressly created to provide climate scenarios for a study of the effect of spatial scale of climate scenarios on agriculture in the southeastern United States, the subject of many of the papers in this Special Issue of Climatic Change. We describe and analyze the coarse (from the CSIRO GCM) and fine scale (from the regional model RegCM) climate simulations, and present the formation of the scenarios to act as input to a number of crop models for an intergrated assessment of climate impacts on agriculture in the southeastern U.S.

The analysis presented in this paper focuses on precipitation and near-surface air temperature, usually the two most important variables used in crop models. We analyze the control runs of both the GCM and the regional climate model (RCM) regarding model biases and provide some dynamical explanations for the control runs' departures from observed climatology. We then go on to discuss the doubled CO_2 simulations, particularly the simulated changes in precipitation and temperature that form the basis of the climate scenarios created for use in the crop models. We stress that the simulations are not intended to provide 'predictions' of climate change. This would require ensembles of transient simulations with different GCMs and nested regional models. Rather they provide the perturbed climate input for use in an uncertainty analysis of the effect of spatial scale of climate scenarios on an integrated assessment of agriculture.

In Section 2 we describe the climate models and the climate runs produced. The control runs are analyzed and validated in Section 3, while the doubled CO_2 runs and scenarios formation are discussed in Section 4. In Section 5 we consider signal-to-noise issues related to the run lengths. Summary and conclusions are presented in Section 6.

2. Models and Experiments

2.1. DESCRIPTION OF MODELS USED

For this work we used the NCAR RegCM of Giorgi et al (1993a,b) driven by output from the control and equilibrium $2 \times CO_2$ simulations with the CSIRO Mark 2 GCM (Watterson, 1998; Watterson et al., 1997, 1999). The GCM was run at R21 horizontal spectral resolution (about 5° in physical space) with nine levels in the vertical and complete physics representation. It uses an Arakawa moist adjustment parameterization of deep convection and includes shallow convection. Cloud cover is determined in three layers and is a function of relative humidity. In addition to parameterizations for the surface boundary layer, soil moisture, and snow cover, it includes ice dynamics with a prognostic open-water fraction in sea ice (Watterson et al., 1997). Land grid squares are partitioned into bare soil and vegetation fractions (Kowalczyk et al., 1994). The atmospheric model is coupled to a 50 m depth mixed layer ocean. Thirty years of control (using a CO_2 concentration of 330 ppmv) and doubled CO_2 runs were produced. The global mean surface temperature increase under $2 \times CO_2$ conditions is 4.3 °C and global precipitation increases by 10%. The global climatology of the control and $2 \times CO_2$ runs are described in Watterson (1998) and Watterson et al. (1999).

The RegCM is an augmented version of the NCAR/Pennsylvania State University mesoscale model MM4 (Giorgi et al., 1993a,b). It is a primitive equation σ vertical coordinate, grid point limited-area model with compressibility and hydrostatic balance. Physics parameterizations incorporated into the model for application to climate studies include the BATS surface package (Biosphere-Atmosphere Transfer Scheme, Dickinson et al., 1993), an explicit planetary boundary layer formulation (Holtslag et al., 1990), a detailed atmospheric radiative calculation package (Briegleb, 1992), a mass flux cumulus parameterization scheme (Grell et al., 1994), and a simplified explicit moisture scheme including an equation for cloud water (Giorgi and Marinucci, 1996). The RegCM was previously nested in the same CSIRO experiments over the western two-thirds of the U.S. (Giorgi et al., 1998).

The RegCM model domain covers the southeastern U.S. using a Lambert conformal projection with a horizontal grid point spacing of 50 km (Figure 1). Fourteen vertical levels are used between the model top (80 mb), with a vertical resolution of $\sigma = 0.1$ in the troposphere and 5 levels below 1500 meters. The closest sigma level to the 1500 m height is 0.815. The land-use distribution for the model domain was derived from a U.S. Geological Survey data set obtained from a combination of remote sensed and ground based data (Loveland et al., 1991).

The high spatial resolution of the model allows for a clear representation of the Appalachian Mountains and the peninsula of Florida, which is not possible in the GCM (Figures 1 and 2). There is no land grid point in the GCM corresponding to Florida.

2.2. REGCM RUNS

Two continuous simulations were carried out, a 5-year present day (control) run and a five year $2 \times CO_2$ with the RegCM driven by time-dependent lateral meteorological fields from the corresponding CSIRO simulations. The same CO_2 concentrations used in the CSIRO were used in the RegCM runs (330 ppmv and 660 ppmv, respectively). Although longer simulations are preferable to increase the statistical significance of the climate signals, previous experience has shown that the interdecadal variability of equilibrium runs is lower than for transient runs, so that even relatively short simulation periods are sufficient to represent the basic behavior of the models (Giorgi et al., 1994, 1998).

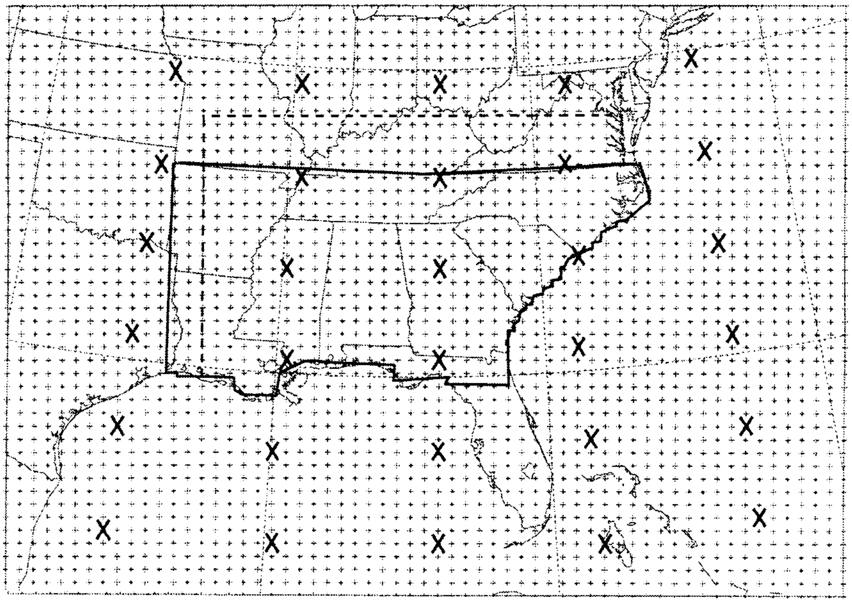

Figure 1. The domain of the regional climate model (RegCM) experiments showing grid points of the RegCM (crosses) and grid points of the CSIRO GCM (large Xs). The area outlined with a heavy solid line is the actual area of the crop study, and the dashed line indicates the climate validation area.

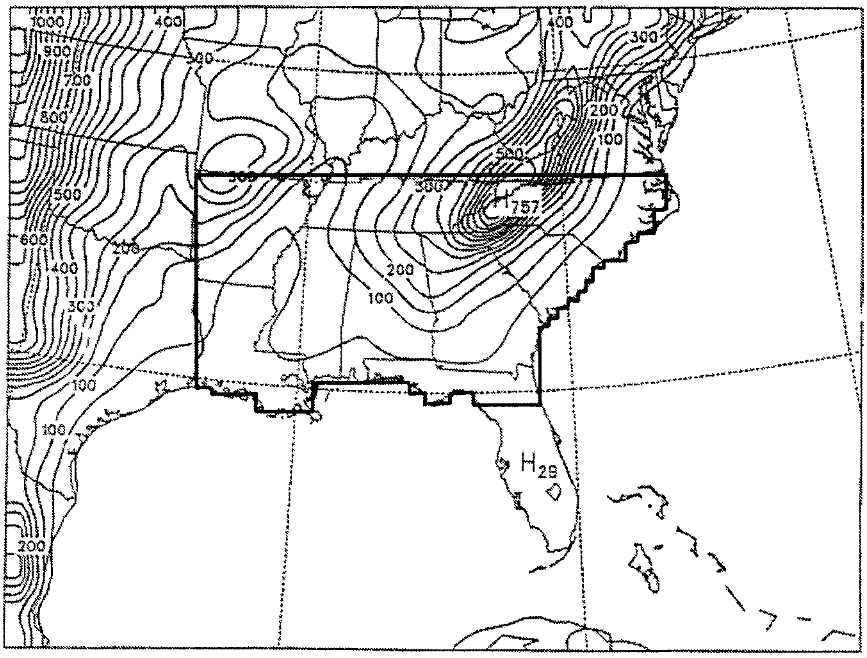

Figure 2. The topography of the RegCM. Contour interval is 50 meters. The area outlined with a heavy solid line is the actual area of the crop study.

The nesting technique is a standard relaxation method for wind, temperature, water vapor and surface pressure applied over a lateral buffer area of 10 grid points, and uses an altitude dependent exponential weighting coefficient for the relaxation terms (Giorgi et al., 1993b). The GCM forcing data were provided at 8 hour intervals, with linear interpolation to each model time step (3 minutes). In the RegCM runs, initial soil water content was interpolated from the GCM normalized soil water content, and time dependent sea surface temperatures were interpolated from the ocean component of the GCM.

Although we do not have available a RegCM simulation driven by analyses of observations for the present domain, an indication of the model performance over the eastern U.S. can be obtained from the work of Giorgi and Shields (1999). They carried out a three year simulation for a domain encompassing the whole continental U.S. with the RegCM driven by ECMWF analyses of observations. Giorgi and Shields (1999) present an analysis of this experiment for different subregions, one of which is the Eastern U.S. They show that the model exhibits seasonally averaged biases in the range of –25.3% (winter) to 17.9% (spring) for precipitation and –1.66 °C (summer) to –0.66 °C (winter) for surface air temperature. Therefore, the model exhibits a generally good simulation of seasonal precipitation and a tendency of a cold bias of a few degrees or less over the region. Giorgi and Shields (1999) also show that the model driven by analyses of observations performs well in reproducing the interannual variability of both seasonal precipitation and temperature over the Eastern U.S.

2.3. DEVELOPMENT OF THE OBSERVED DAILY CLIMATE DATA

We developed the data set to serve as a validation data set for the regional climate model in the Southeast, and to serve as the climatological input for crop models that were to be applied over the Southeast under observed and perturbed climate conditions. We developed the observed data set on the grid of the RegCM, covering the states that were to be included in the impacts study (outlined on Figure 1). We did not include the lower peninsula of Florida since the density of stations was low, and many sites had large amounts of missing data. Moreover, this part of Florida, where mainly vegetables are grown, was not highly relevant to the crops we planned to model. Furthermore, since there is no comparable land area in the CSIRO GCM, use of this area in the comparative validations of the control runs would lead to spurious results, and it would be difficult to develop a credible climate change scenario from the CSIRO for this area, which is represented by an ocean grid point. Variables on a daily time scale included maximum and minimum temperature, precipitation, relative humidity, solar radiation, and wind speed. Temperature and precipitation were taken from the U.S. daily cooperative station data set available at NCAR (DS 510.0), which corresponds to the NCDC data set TD3200 U.S. Control Summary of Day. Only stations having less than 10% missing precipitation data for the time period 1960–1995 were considered for use. The station having less than 10% missing data and closest to the center of each RegCM 50 km grid was selected to represent the grid. Missing precipitation data were filled by taking the median of precipitation for stations (three or more) within a 0.5 degree radius from the primary station. Missing temperature data were filled by taking the average of temperature from these surrounding stations. The other variables, solar radiation, relative humidity, and wind speed were generated using the weather generator available with one of the crop models used (Richardson and Nicks, 1990). Mean monthly data for these variables available as part of an EPIC crop model data set also served as input to the weather generator. Generated solar radiation data were spot-checked using the sparse network (30 stations) of daily observed radiation stations in the Southeast (NREL, 1992).

3. Evaluation of Control Runs

We evaluated the control runs of the RegCM and CSIRO using several different observed data sets: the daily data set (described in Section 2.3 above), the Legates and Willmott data sets (Legates and Willmott, 1990a,b, referred to as LW) and the University of East Anglia (UEA) data set (New et al., 1999, 2000). The LW data set was used initially while running the regional climate model to evaluate the model performance for each year of the run. That data set includes only mean monthly temperatures and precipitation, assembled from data sets covering varying time periods, but includes both land and ocean. The daily data set is used with a statistics package (Mearns et al. 1995a,b) to statistically evaluate both the CSIRO and RegCM control runs and other contrasts. Since the model runs are relatively short (5 years), it is particularly desirable to use statistics that consider daily data.

We used the University of East Anglia (UEA) (New et al., 1999, 2000) data set to expand the coverage of the evaluation, since the daily data set was only developed for the part of the regional climate domain that was used for the impacts study. The UEA data set, which is a monthly data set, developed on a 0.5 degree grid, covers 1900–1995. We used the subset of years 1960–1995, the same set of years as the daily data set. The UEA data set contains monthly time series of mean maximum and minimum temperature and precipitation for the full time series. However, it is a land only data set. The UEA monthly data set was bilinearly interpolated to the RegCM grid, which has a similar spatial resolution.

The arrangement of the CSIRO grids is such that only 5 complete grids are contained in the impacts study area. Using the UEA data we were able to look at a larger portion of the domain, covering 8 complete CSIRO grids to get a more complete picture of the CSIRO model performance (outline on Figure 1). We did not include the western most CSIRO grids in our evaluation of control runs since only their eastern edges were in the study area, and the far western parts of these grids fell within the interpolation buffer zone. We compared the daily data set and the UEA data set on a monthly and seasonal time scale and found them to be very similar both for temperature and precipitation. Precipitation estimates in general differed by 1% or less and temperatures by 0.25 °C.

3.1. DOMAIN WIDE EVALUATION USING THE UEA DATA SET

The CSIRO was originally chosen for this nesting work since it reproduced relatively well the general climatology over the continental U.S. as represented by the L&W data set.

Reproduction of the climatology of the southeastern U.S. is often challenging for climate models because of a number of factors: the importance of convective precipitation in the region; the complexity of the moisture sources for precipitation (Gulf of Mexico and the Atlantic Ocean); the location and strength of the Bermuda high; the location and strength of the nocturnal jet; and the importance of contributions to precipitation from hurricanes along the coast in late summer (Robinson and Henderson, 1992; Henderson and Vega, 1996).

As a result of these various processes, precipitation over the southeastern U.S. shows different seasonality over different areas of the region (see Figures 3a–d). In the winter (Figure 3a), precipitation is maximum over Louisiana and the southern half of Mississippi and Alabama. Maximum precipitation is also found over the Appalachians, with precipitation decreasing towards the north and west of the region. The basic features of this precipitation pattern do not change much in the spring (Figure 3b), although the westward gradient of precipitation is less pronounced than in the winter. The precipitation patterns change dramatically in the summer (Figure 3c), when maximum precipitation is found over the coastal regions, both on the Gulf of Mexico and the Atlantic. A secondary, but not pronounced maximum in summer precipitation still occurs over the Appalachians, while again precipitation decreases towards the west. Finally, another major shift in precipitation patterns occurs in the fall (Figure 3d), when the region overall experiences its driest conditions, especially over Georgia, South Carolina and North Carolina, and a maximum is shifted towards the west over western Louisiana and Arkansas.

Concerning temperature (not shown), as expected the region shows a north to south positive gradient and a pronounced seasonal cycle. Observed average temperatures over the validation domain varied from about –2 °C to 14 °C in the winter to about 18 °C to 28 °C in the summer. The diurnal temperature range is also pronounced, in the range of 10–14 °C in all seasons. The Appalachians are also clearly identified by the lower temperatures (2–3 °C) compared to the surrounding regions at the same latitudes.

Table I presents the average seasonal biases (using the UEA data as the observed data) for both model control runs over the central domain, which extends further to the north than the study area in order to include all of the northern CSIRO grid boxes.

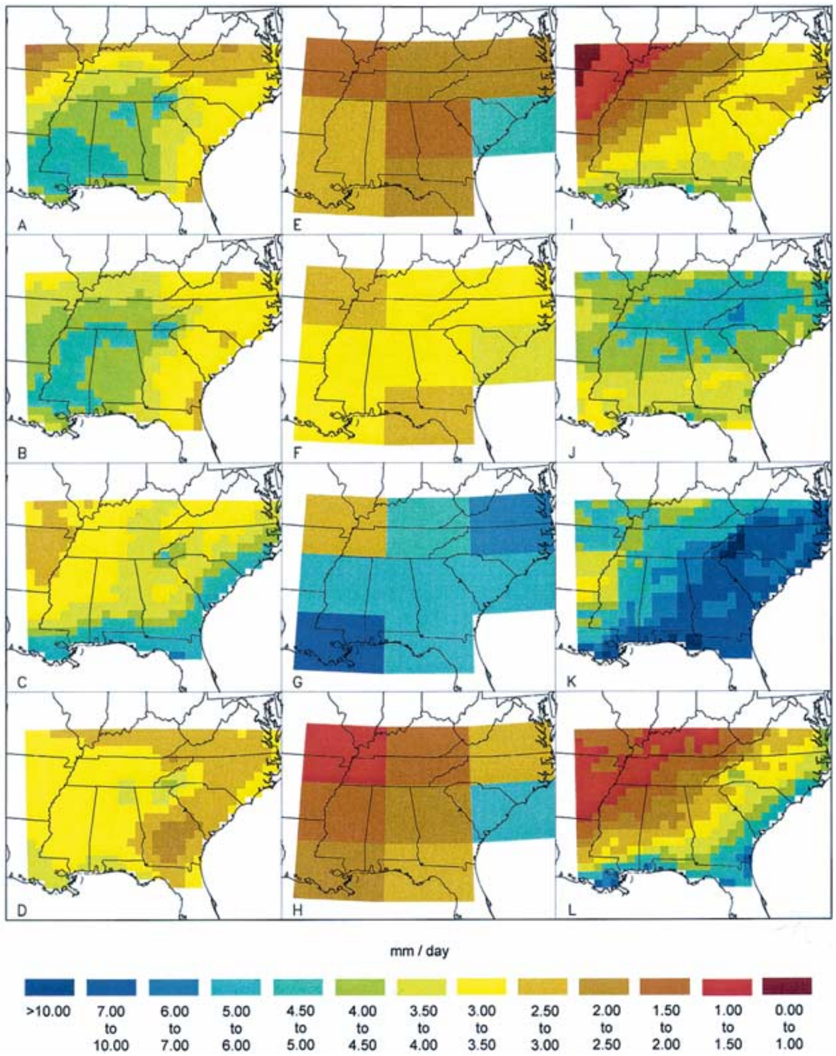

Figure 3. Maps of seasonal precipitation (mm/day) for winter, spring, summer and fall for UEA observations (a–d); CSIRO control run (e–h); and RegCM control run (i–l).

The biases are calculated for each season by averaging over this domain slightly larger than the study area. For temperature we focus on daily maximum and minimum temperature since the average can be affected by compensating errors in the maxima and minima. Overall there are, as is often the case, general similarities in the biases produced by the GCM and the RCM aggregated over the region (Table I). Both models have cold biases in maximum temperature and cold or warm biases in minimum temperature during most of the year. The CSIRO, however, has uniformly larger (and positive) biases in minimum temperature. Note that in all seasons, the biases in the RegCM are smaller than those in the CSIRO, especially

Table I

Southeast domain average biases in the control run climates of the CSIRO and RegCM2 (5 years each), compared with the UEA observed data (1961–1995)

	Maximum temperature (°C)	Minimum temperature (°C)	Precipitation (%)
Winter			
CSIRO	–2.8	0.9	–30.7
RegCM	–2.3	–0.4	–26.4
Spring			
CSIRO	–3.5	1.5	–13.6
RegCM	–2.8	–0.7	16.5
Summer			
CSIRO	–2.4	2.7	36.0
RegCM	–1.6	–0.0	60.6
Fall			
CSIRO	–2.4	2.9	–19.6
RegCM	–1.6	0.8	–8.9

CSIRO indicates results where the UEA data were aggregated to the CSIRO and then the comparison done at that scale.

for the minimum temperature. This improvement is likely not due to the increase in resolution in the RegCM, but rather to the effect of the different land surface schemes in the models. The BATS scheme used in the RegCM and the land surface scheme used in the CSIRO (Kowalczyk et al., 1994) are of similar structure and complexity. However they use different vegetation parameters and drag coefficient formulations, so that these can affect the model results.

Note that Table I implies that the diurnal temperature range as calculated by the RegCM is generally more pronounced than that calculated by the CSIRO. In addition to the use of different land surface schemes, another contribution to this result may come from differences in the simulation of cloudiness.

The spatial patterns of biases in temperature for the RegCM are the following (not shown for brevity). In winter and spring there is a gradient of negative bias in maximum temperature going from values of around –1 °C in the western part of the subregion (western Arkansas) to values up to –5 °C in a small portion of the the northeastern part of the domain (N. Carolina). In summer and fall biases progress from slightly positive in the western part to about –5 °C in Georgia. A possible factor that would contribute to the general underestimation of maximum temperature by the RegCM is related to the simulation of clouds. It has been noted (e.g., Giorgi et al., 1999) that the RegCM has a tendency to simulate excessively high cloud optical thicknesses when clouds occur. Especially in the presence of daytime convective cloudiness this would lead to a decrease in maximum temperatures. Minimum temperatures are generally overestimated in the fall up to 2 °C in the western part of the domain. In summer, minimum temperature biases vary between + and –1 °C, with no set spatial pattern. In spring and winter largest minimum temperature biases are again found in the northeastern part of the domain (N. Carolina) but values do not exceed 3 °C.

Biases in maximum temperature for the CSIRO are negative throughout the southeast area in spring, summer, and fall (not shown). In spring the largest bias is in the northeastern part of the domain (about –4 °C). A similar pattern is seen in the summer. In fall the largest biases are found in the southcentral area (e.g., Alabama). In winter the largest negative biases, around –5 °C, are seen in the northcentral area (Tennessee). The patterns of biases in minimum temperature are similar for spring, summer, and fall, with largest positive biases in the eastern grids, reaching about 4 °C in summer. In winter the biases are mixed positive and negative.

Moving to precipitation (Table I), region-averaged precipitation biases of both models are negative in the winter and fall, and positive in the summer. In the spring the biases are of opposite sign and are relatively small. The biases in the models are similar in the two cold seasons, but the positive bias of the RegCM in summer is larger than that of the GCM. The magnitude of these biases is generally similar to that of the CSIRO and the RegCM for the central Great Plains analyzed by Giorgi et al. (1998), except in the summer for the RegCM.

To better understand these biases we can compare the CSIRO and RegCM seasonal precipitation, shown in Figures 3e–l, with the observations of Figures 3a–d. In winter, both models capture the northwestward negative precipitation gradient towards the Central Plains. However, this extends too far south and east in the models. In addition, precipitation is also undersimulated over the central and eastern regions of our study area, where however, the RegCM results are closer to observations than the CSIRO's.

In the spring the CSIRO underestimates precipitation throughout the domain except for one grid in the east (Figure 3f). The magnitude of RegCM precipitation is more in line with observations (Figure 3j), although the maximum in the RegCM shifts to the northeast of the observed one. Note that the maximum precipitation along the crest of the Appalachians is captured by the RegCM. This is due to orographic uplift of air within the eastward travelling storm systems and possibly to convective activity induced by the solar heating of high elevation surfaces (e.g., Giorgi, 1991).

Differences in warm season precipitation between the RegCM and CSIRO may be due to two reasons; either the use of different convection schemes or the increase in resolution. For example, Giorgi and Marinucci (1996) showed that the same convection scheme tends to produce higher localized precipitation events as the resolution increases. These events are to some extent self-feeding through the release of condensation heat. This process may be responsible for the greater precipitation amounts found in the RegCM over the Appalachian region in addition to the orographic uplift and high elevation surface heating effects. A possible mechanism for the northeastward shift of the precipitation maximum, which has been also noted in previous RegCM runs (e.g., Giorgi and Shields, 1999) is that the RegCM version used in the present run exhibits deficiences in simulating the effects of mesoscale convective complexes. This problem has been noted in many regional models (e.g., Takle et al., 1999), although parameterizations are now available in the RegCM that considerably ameliorate it (Pal et al., 2000).

Moving now to the summer case, we can notice that, consistent with the observations, the models shift the precipitation maximum to the southeast portions of the study area. It is evident, however, that both models heavily overestimate precipitation over this region. The similarity of the RegCM and CSIRO patterns indicate that the regional model is likely inheriting this bias from the CSIRO and amplifying it possibly through the resolution effect discussed above. Since most of the water vapor input to the region during the summer originates from the Gulf of Mexico, it is likely that the precipitation overestimation is due to excessive southerly water vapor flux.

Finally, both models generally underestimate precipitation during the fall (Figures 3h,l), particularly in the western half of the domain. Again, this seems mostly a result of the bias in the CSIRO simulation which is transmitted to the RegCM. The RegCM produces somewhat higher precipitation amounts over the region than the CSIRO, which brings it closer to observations.

Pan et al. (2001) used essentially the same version of the RegCM as in our experiments and found that the RegCM tended to underestimate cold season precipitation over the southeastern US when driven by NCEP reanalyses and to overestimate it when driven by the HadCM. This illustrates the strong impact of the boundary forcing on the precipitation simulation. In the warm season the precipitation biases were small for the reanalysis-driven runs and positive in the HADCM-driven runs. In all seasons the RegCM tended to simulate greater precipitation amounts than the HADCM, a result in line with the present experiment.

3.2. STATISTICAL TESTS USING DAILY DATA

To determine the statistical significance of the differences described above we used the observed daily data set for the same time period of the smaller domain area and applied a domain statistical package (Mearns et al., 1995a,b) that uses daily data as input. By using statistics for daily data, we take advantage of a a larger sample size than if we used tests for mean monthly data. We analyzed the results of tests on mean daily maximum and minimum temperature and mean daily precipitation for each month. As presented in Katz (1982) statistical inferences regarding mean daily temperature may be made using the following test statistic:

$$Z = \frac{\overline{X}_2 - \overline{X}_1}{[n_2^{-1}\hat{V}^2(2) + n_1^{-1}\hat{V}^2(1)]^{\frac{1}{2}}}\,, \tag{1}$$

where $\overline{X}_1$ and $\overline{X}_2$ = the estimated means of time series 1 and 2; n_1 and n_2 = sample size of time series 1 and 2; $\hat{V}^2$ = estimated variance of time series 1 or 2 defined by:

$$\hat{V}^2 = \frac{\hat{\sigma}_a^2(p)}{[\sum_{k=0}^{p}\hat{\phi}_k(p)]^2}\,, \tag{2}$$

where $\hat{\sigma}_a^2(p)$ = estimated innovation variance from an autoregressive process of order p; $\hat{\phi}_k(p)$ = the estimated autocorrelation coefficient of order p, $k = 0, p$.

In this instance we fit a first order autoregressive process to the temperature time series, i.e., $p = 1$. Under the null hypothesis the statistic converges to a standard Gaussian distribution as the sample sizes both tend to infinity.

For precipitation the test statistic is formulated using parameters of both the frequency and intensity aspects of daily mean precipitation. First the right skewed precipitation intensities are logarithmically transformed. The test is constructed with the transformed data.

$$Z = \frac{\overline{Y}_2 - \overline{Y}_1}{[n_2^{-1}\hat{V}^2(2) + n_1^{-1}\hat{V}^2(1)]^{\frac{1}{2}}}\,, \tag{3}$$

where $\overline{Y}_1$ and $\overline{Y}_2$ = the estimated means of the (log transformed) daily precipitation time series 1 and 2; n_1 and n_2 = sample size of time series 1 and 2; $\hat{V}^2$ = estimated variance of time series 1 or 2.

The estimated variance term is a complex function of transition probabilities (concerning the frequency process) and characteristics of the intensity of precipitation (rain falling on rain days) and is given in Katz (1983) in Equations 31–37.

We use these tests as a general diagnostic to compare the control versus observed climatologies for the two models. There are some statistical issues to consider. First, the tests are performed simultaneously at multiple grids, creating the problem of multiplicity. For any given significance level (e.g., 0.05) one would expect that for at least some of the locations (5%), the null hypothesis would be rejected by chance. Furthermore, there is the problem of spatial correlation of the variables being tested across the grids. We, however, do not use these tests for formal hypothesis testing, but rather as a general diagnostic for comparing the CSIRO and RegCM results. We display the percentage of the domain where significance at the 0.05 or higher level is attained for each model, for each month (Table IIa).

The months that resulted in the largest percentage of the domain with significant (at the 0.05 level) differences between the model control run and observations

Table II

Percent area for precipitation

		Month											
		1	2	3	4	5	6	7	8	9	10	11	12
a. Control versus observations (daily observed dataset)													
CSIRO	+	12.5	12.5	0.0	37.5	75.0	50.0	87.5	87.5	62.5	25.5	12.5	0.0
	–	62.5	50.0	62.5	0.0	0.0	0.0	0.0	0.0	12.5	37.5	50.0	87.5
RegCM	+	0.0	14.1	2.7	48.9	31.3	48.4	88.6	52.1	12.8	3.7	11.9	1.2
	–	56.5	18.0	8.1	0.0	0.2	0.0	0.0	0.0	49.7	56.0	36.8	70.4
b. $2 \times CO_2$ *versus control*													
CSIRO	+	0.0	0.0	37.5	62.5	0.0	0.0	0.0	0.0	0.0	27.3	0.0	0.0
	–	25.0	12.5	0.0	0.0	0.0	0.0	37.5	25.0	50.0	0.0	25.0	12.5
RegCM	+	0.5	0.0	3.1	20.7	24.7	4.0	1.1	0.0	0.2	31.6	0.0	4.0
	–	0.0	40.0	0.0	0.0	0.0	8.7	66.5	48.5	32.9	0.2	6.3	0.7

Percentage area across the southeast small domain (covering 8 CSIRO grids) where significant (at the 0.05 level) differences between the two precipitation datasets indicated were found. + and – refer to whether the contrast is positive or negative, i.e., + = significant positive difference and – = significant negative difference. The total % area at the 0.05 level is determined by adding the values (+ and – categories).

for precipitation (RegCM) were July when virtually all of the domain has significant overestimations of precipitation (Table IIa). In the cold season months of September through January, about one half of the domain showed significant underestimations. February and March produced the best results when few grids reported significant differences between the observed and modelled precipitation.

Results for the CSIRO are somewhat more limited because not all relevant grids are completely covered by the daily observed data set. The percentage biases are based on the large CSIRO grids and the aggregation of the daily values to the CSIRO grid scale. Each CSIRO grid represents 12.5% of the area. Months with largest percentages of the area showing overestimations for precipitation include May through September with highest values in July and August. The seasonal pattern is not dissimilar from that of the RegCM, with large underestimations occurring from November through March (Table IIa). March is the month for the RegCM when very good reproduction of the observed precipitation is seen, but essentially there is no corresponding good month for the CSIRO.

It is important to note from the comparison of Table I and Table IIa that, although the region-average precipitation biases in the RegCM are of similar magnitude as those of the CSIRO, the percentage area in which the bias is statistically significant is smaller in the RegCM than in the CSIRO for most months. Even in July, when the bias is much larger for the RegCM, the percentage area in which this bias is significant is essentially the same in the two models. This result indicates that the RegCM reproduces better the spatial distribution of precipitation and that the region-average RegCM bias is more dominated by the contribution of relatively small areas. This is also evident from the comparison of the seasonal spatial patterns of precipitation discussed in the previous section. In the next section we will provide a more quantitative evaluation of the ability of the models to reproduce the observed spatial precipitation patterns.

Regarding temperature, the RegCM minimum temperature best reproduces observations based on the statistical test, when usually more than half of the domain shows no statistically significant difference with observations (not shown). Maximum temperature, however, is significantly underestimated across most of the domain in every month. The CSIRO displays a similar pattern for maximum temperature, which is usually significantly underestimated, particularly November through June. However, minimum temperature is significantly overestimated at all grids from April through October and at most grids for the rest of the months. These results underscore the better reproduction of temperature overall for the RegCM, particularly of minimum temperature, compared to the CSIRO.

3.3. SPATIAL CORRELATIONS

Table III displays the spatial correlations between simulated and observed temperature and precipitation over the domain both for the CSIRO and RegCM. The CSIRO grid results were interpolated to the RegCM grid for this comparison. An adiabatic adjustment for elevation with reference to the RegCM topography is made for the CSIRO temperatures as part of the interpolation procedure.

For the RegCM, the correlations are generally high, greater than 0.80 both for daily maximum and minimum temperature, and the correlation coefficients are comparable to those obtained for the Great Plains in the simulation of the western two-thirds of the United States (Giorgi et al., 1998). RegCM correlations for minimum temperature are better than those for CSIRO, especially in winter when the CSIRO correlation is only 0.66. For maximum temperature, the correlations are comparable in the two models except for summer, when the CSIRO shows a relatively low correlation (0.50) with observations. Overall, Table III shows that the RegCM improves the simulation of the temperature spatial distribution compared to the CSIRO, even though this domain is not characterized by a strong topographical forcing. However, the better representation of the Appalachian mountains and the complex coastlines does contribute somewhat to the improved simulation of temperature. The adiabatic correction of temperature for the CSIRO mitigates the difference in the resolution effect between the two models for the correlations with temperature observations.

RegCM correlations for precipitation are highly variable, ranging from good correlations in summer and to a lesser extent in winter to poor correlations in spring and fall (Table III). These precipitation correlations reflect a poorer spatial repre-

Table III

Spatial correlations observed (UEA) versus CSIRO and RegCM 5-year control runs

	Maximum temperature (°C)	Minimum temperature (°C)	Mean temperature (°C)	Precipitation (%)
Winter				
CSIRO	0.97	0.66	0.93	0.10
RegCM	0.94	0.95	0.95	0.43
Spring				
CSIRO	0.91	0.92	0.95	–0.13
RegCM	0.95	0.96	0.97	0.16
Summer				
CSIRO	0.50	0.85	0.82	0.52
RegCM	0.81	0.96	0.93	0.76
Fall				
CSIRO	0.95	0.86	0.93	–0.21
RegCM	0.86	0.95	0.93	0.01

sentation than was produced for the Great Plains in the aforementioned run (Giorgi et al., 1998), except in summer when results are similar. The spatial correlations are not aligned with the mean biases. The large mean bias in summer, for example, corresponds with a relatively good spatial correlation, whereas the small mean bias in spring corresponds to a poor spatial correlation. This is because, as discussed above, the region-averaged bias may be dominated by the contribution of relatively small regions.

The precipitation correlations of the CSIRO with observations of precipitation are uniformly lower than those for the RegCM in all seasons. However, both models poorly reproduce the pattern of precipitation in spring and fall when, evidently the RegCM cannot compensate for the errors deriving from the large scale forcing. We can conclude from these results that the RegCM overall produces better spatial patterns of temperature and precipitation than does the CSIRO, and in that regard improves on the regional simulation of climate compared to the CSIRO. This result has been found consistently in nested regional climate simulations with different models (Giorgi and Mearns, 1999). However, when the large scale forcing is substantially biased, such as for spring and fall precipitation, the bias is inevitably transmitted also to the regional model.

Table IV

Southeast domain average seasonal climate changes ($2 \times CO_2$ versus control) of the CSIRO and RegCM (5 years each)

	Maximum temperature (°C)	Minimum temperature (°C)	Mean temperature (°C)	Precipitation (%)
Winter				
CSIRO	4.0	4.5	4.3	–18.9
RegCM	3.7	3.7	3.7	–1.5
Spring				
CSIRO	4.6	5.6	5.1	35.7
RegCM	4.1	5.3	4.7	26.5
Summer				
CSIRO	4.2	3.8	4.0	–17.0
RegCM	5.1	3.7	4.4	–30.9
Fall				
CSIRO	4.7	3.9	4.3	–7.2
RegCM	5.2	4.0	4.5	2.7

4. $2 \times CO_2$ Control Climates

4.1. SEASONAL RESULTS

Table IV shows the area-average seasonal temperature and precipitation changes for the CSIRO and RegCM. On an area wide basis most striking changes occur in spring and summer for precipitation, with similar general tendencies in the two models.

Substantial precipitation increases are seen for both models in the spring, but substantial decreases in the summer. The CSIRO experiences larger increases in the spring than the RegCM but the latter model experiences larger decreases in the summer. The precipitation changes in the fall and winter seasons are relatively small, especially in the RegCM. Area wide average changes in temperature are similar in the two models (Table IV). Temperature changes are largest for spring minimum temperature (greater than 5 °C), and smallest for summer minimum temperature.

Detailed spatial contrasts between the climate changes are, however striking. The spatial distribution of the regional changes in precipitation is shown in Figure 4. In spring, the percentage changes in precipitation across the domain are not dissimilar for the two models, both showing increases throughout the area

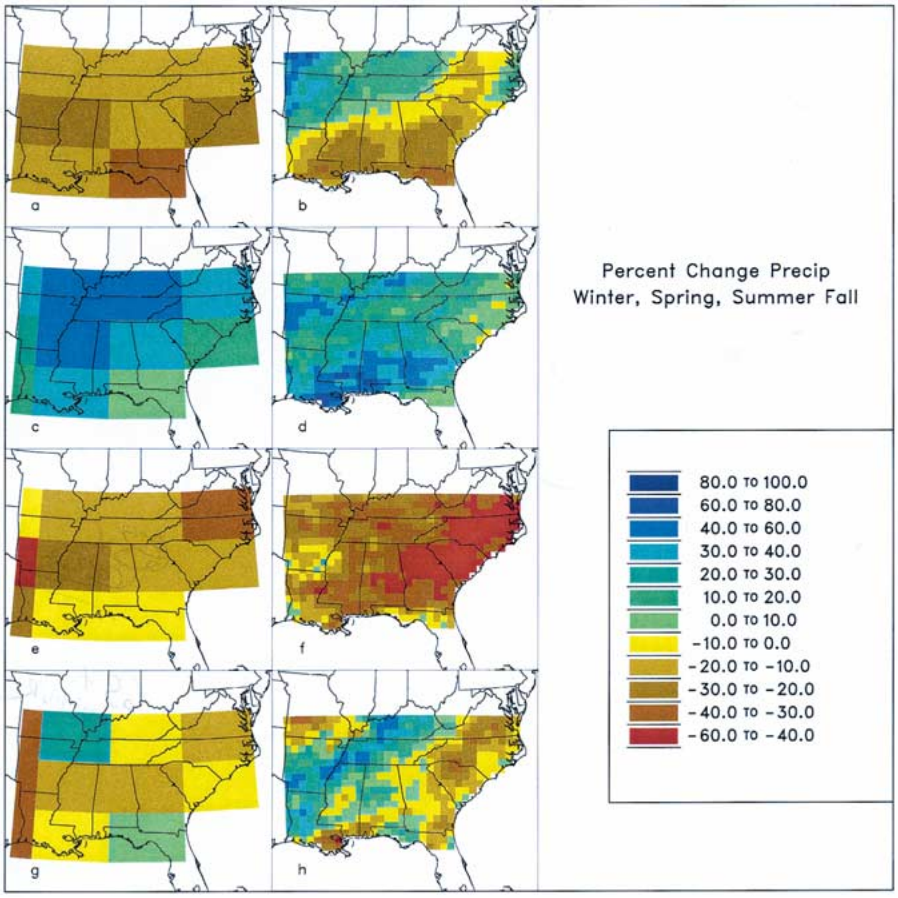

Figure 4. Percentage change ($2 \times CO_2$ – control/control) in seasonal precipitation for winter (a) CSIRO, (b) RegCM; spring (c) CSIRO, (d) RegCM; summer (e) CSIRO, (f) RegCM; and fall (g) CSIRO, (h) RegCM.

(Figures 4c,d). These increases are due to greater southerly water vapor fluxes over the region in the $2 \times CO_2$ simulation (not shown). However, differences between the spatial patterns of change in the CSIRO and RegCM are simulated. The CSIRO shows maximum increase of precipitation in the upper Mississippi Valley and Tennessee. The RegCM also shows a maximum of precipitation increase in the same region (although less extended than in the CSIRO), but in addition it simulates an area of large increase extending over the lower southcentral area of the region of interest (Figures 4c,d).

In summer, while both models show decreases throughout the area, the spatial patterns of these decreases are quite different (Figures 4e,f). Very large decreases in precipitation are found all along the eastern coastal plain for the RegCM (as much as 50%) whereas the changes in the CSIRO are more uniform across the domain with the largest changes over North Carolina and Virginia. Note that the region of maximum precipitation decrease in the RegCM corresponds to the region of maximum precipitation in the control run (see Figure 3h). Figure 6 shows the vertically integrated average summer water vapor fluxes (calculated from 6 hour samples) in the control and 2 $\times$ CO_2 experiments for both the CSIRO and the RegCM. Both models show in the 2 $\times$ CO_2 runs a minimum in water vapor flux occurring over the Gulf of Mexico off the coast of Florida. This causes a general decrease in southerly water vapor flow from the gulf regions to the southeastern U.S. which is most likely responsible for the simulated decrease in precipitation. Also note that in the RegCM this low in moisture flux is located farther north than in the CSIRO, which helps explain the greater precipitation decrease found in the regional model.

In winter the CSIRO experiences decreases in precipitation throughout the area (Figure 4a), while the RegCM experiences decreases in the southeastern half of the area, but precipitation increases across Arkansas and Tennessee (Figure 4b). Previous nested modeling experience has shown that, although the large scale features in the nested and driving models are generally similar, shifts in large scale circulations (e.g., storm tracks) can occur in the interior of the nested model domain (Jones et al., 1995; Giorgi et al., 1998). In our simulations the difference between CSIRO and RegCM precipitation change is due to a southerly shift of an area of increased precipitation that in the CSIRO only reached the central regions of Missouri and Kansas. Finally, in the fall (Figures 4g,h) both models show a decrease in precipitation over the southeastern coastal states and an increase in precipitation over the Upper Mississippi River Basin region included in the area of interest, although this increase extends further south in the RegCM.

For temperature the largest spatial contrasts in change are found in summer maximum temperature, when the RegCM exhibits large increases in temperature in the northeastern part of the domain (roughly corresponding to areas of the largest precipitation decrease), whereas the CSIRO exhibits uniform changes of between 4 and 5 °C throughout the area (Figures 5g,h). Changes in the RegCM vary from 3 to 4 °C in the southwest part of the area up to around 7 °C in the northeastern part of the study area. Interestingly, minimum temperatures in summer for the RegCM show rather uniform changes of around 4 °C across the study area (Figure 5f). A similar uniformity in change is seen for the CSIRO (Figure 5e). The large increases in maximum temperature for the RegCM in summer results from the extreme soil moisture drying that occurs because of the large decreases in precipitation. This results in large decreases in latent heat flux, and increases in sensible heat flux at the surface, and thus warming of the air above. Another notable contrast in temperature is seen in spring minimum temperature for the CSIRO (Figure 5a) when increases between 6 and 7 °C in the northern portion of the study area are seen. This increase is less pronounced in the RegCM (Figure 5b) and is largely lacking in the maximum temperatures (Figures 5c,d).

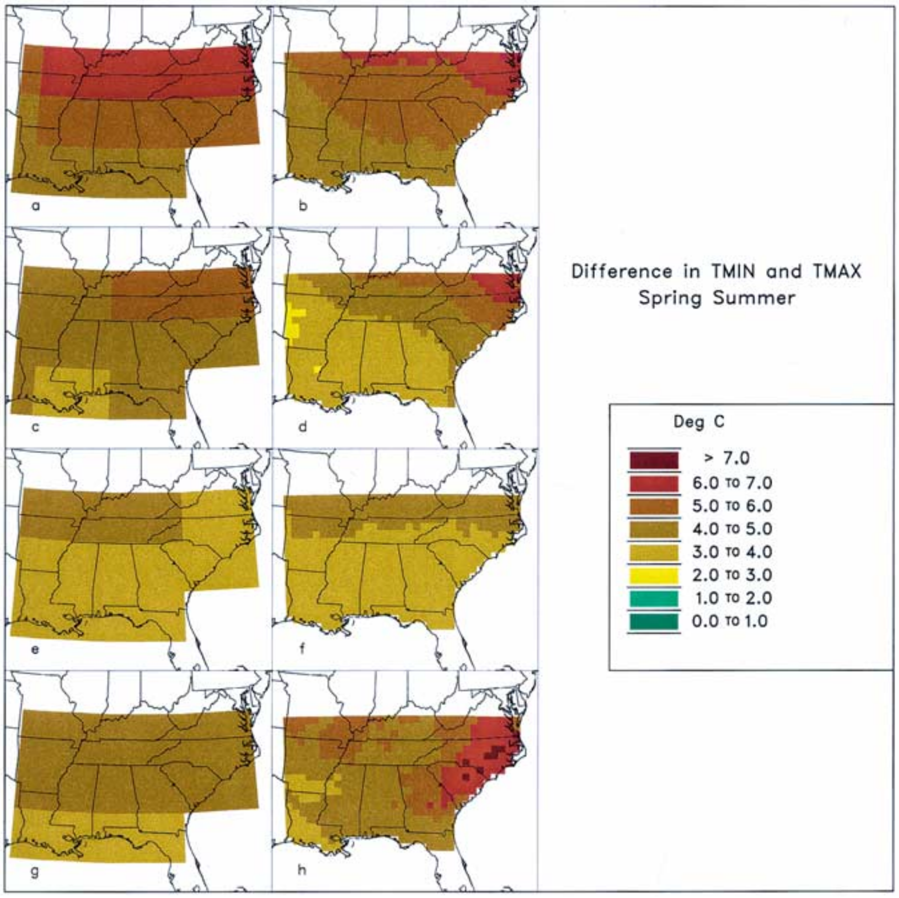

Figure 5. Changes (2 × CO_2 – control) in minimum and maximum temperature (°C) for the CSIRO and RegCM for spring (a) CSIRO minimum, (b) RegCM minimum; (c) CSIRO maximum, (d) RegCM maximum; and summer (e) CSIRO minimum, (f) RegCM minimum; (g) CSIRO maximum, (h) RegCM maximum.

Temperature changes in the winter and fall are similar for both models (remaining around 4 or 5 °C) except in the fall maximum for the RegCM on the east coast, which resembles the pattern of summer (not shown).

4.2. STATISTICAL ANALYSIS OF MONTHLY CHANGES

The same statistical package used in comparing the control and observed precipitation and temperatures for both models, is used here to compare the 2 × CO_2 and control results. Table IIb presents the percentage of the domain found to have significant differences 2 × CO_2 – control in mean precipitation for each month for the two models.

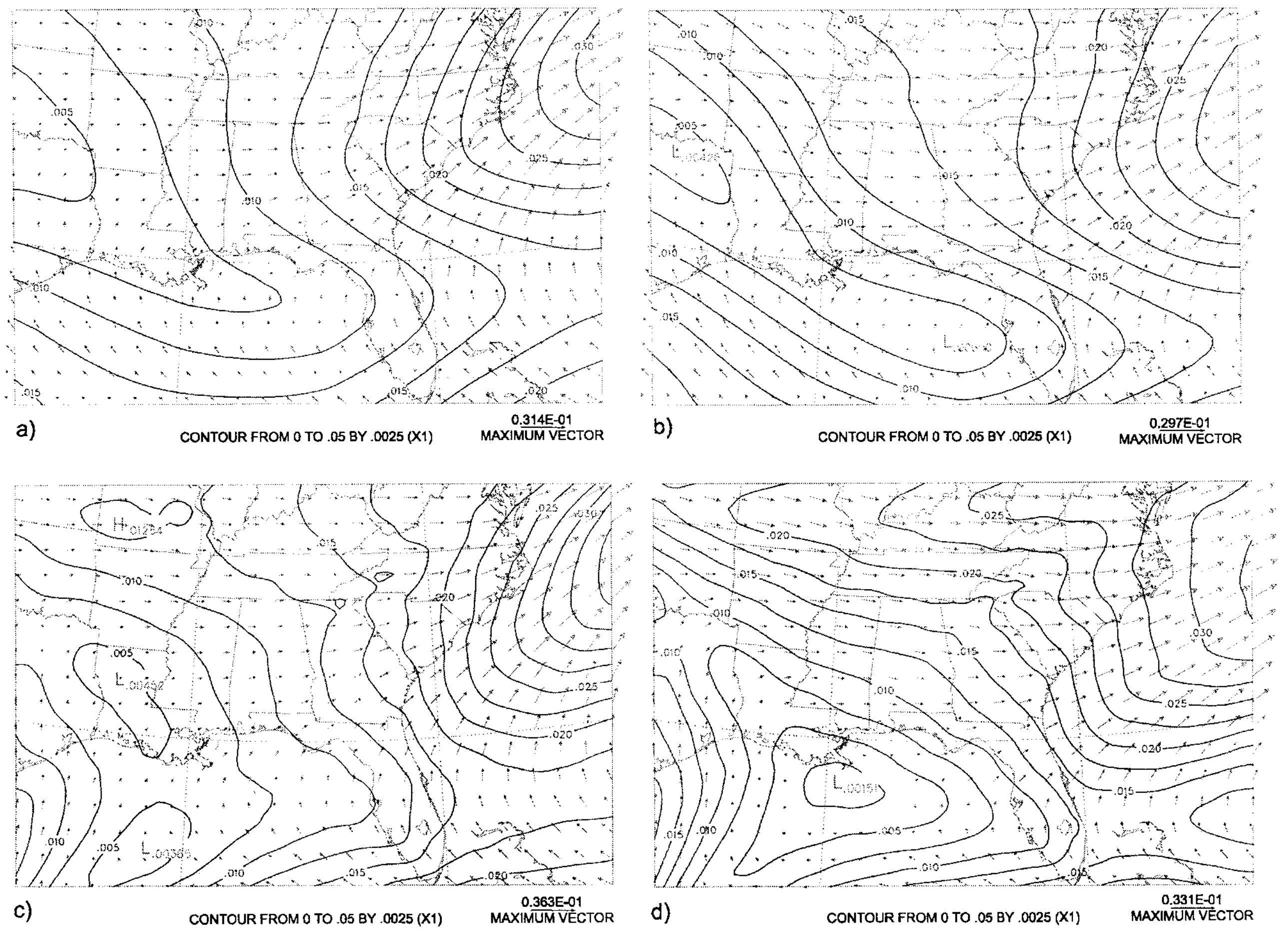

Figure 6. Vertically integrated moisture flux in summer: (a) CSIRO control, (b) CSIRO 2 × CO_2, (c) RegCM control, and (d) RegCM 2 × CO_2. Units are kg/kg m/s.

Again each CSIRO grid represents 12.5% of the southeast area considered. Based on the percentage area that exhibit significant changes, most significant decreases in the CSIRO simulation are seen in July through September, while most significant increases are seen in March and April.

For the RegCM, a similar pattern of significant decreases is seen in July through September, while the pattern of significant increases in the spring months differs from that of the CSIRO. In March and April the CSIRO shows much greater areas with significant increases, while the opposite occurs in May. In general the pattern of significant increases reflects the greater spatial variability and greater intensity of changes seen in the RegCM compared to the CSIRO.

All maximum and minimum temperature changes are significant for both models for all months (not shown). However, there are some interesting contrasts of degree of change on a monthly time scale. In particular in May in the RegCM rather small increases in temperature tend to dominate in the area where precipitation increases substantially in the southcentral subregion. This strong association between changes in temperature and precipitation in the RegCM is not as evident in the CSIRO.

4.3. FORMATION OF THE TWO CLIMATE SCENARIOS

To form the two scenarios to be used as input to crop models, the standard procedure of combining the change in climate from the climate models with the baseline observed climate data set was used. For maximum and minimum temperature, monthly average values of differences ($2 \times CO_2$ – control) were calculated. For the other variables (precipitation, solar radiation, relative humidity, and wind speed), the ratio $2 \times CO_2$/control for each month was calculated. These differences or ratios were then combined with the daily values of the observed data set. For example, the monthly difference in maximum temperature would be added to each daily value of observed maximum temperature. For temperature this procedure changes the mean of the temperature time series, but the variance (both daily and interannual) is unchanged. For precipitation, the daily values of observed precipitation are multiplied by the ratio for the particular month in question. Thus, the frequency of precipitation is not changed, but the mean of the daily intensity is changed by the ratio, and the variance of the intensity is changed by the square of the ratio. The two different resolutions of climate scenarios are produced based on the spatial resolution of the changes in climate. The changes in climate are combined with the baseline climatology with a resolution of 0.5 degrees. For the coarse (CSIRO) resolution scenario, then, the observed climatologies at all 50 km grids contained within a given CSIRO grid box are combined with the same set of climate changes (on a monthly basis). For the fine resolution (RegCM) scale scenario, each 50 km grid observed climate is combined with the unique set of climate changes from the RegCM grid corresponding to that location.

4.3.1. *Changes in Other Variables*

While this paper mainly concerns precipitation and temperature, we make a few comments here on the changes in some other variables (solar radiation, relative humidity, and wind speed) in the two different climate projections. All crop models applied in the various projects use solar radiation as an input, and some use relative humidity and wind speed. Changes in solar radiation are highly correlated with changes in precipitation, i.e., solar radiation increases where precipitation decreases. The changes in solar radiation, however, are relatively small, mostly within + or –10%.

In certain months, such as the summer months when both models experience large decreases in precipitation, increases in solar radiation can be up to 30%. The detailed spatial variability of these changes tend to be larger in the RegCM, but mean patterns across the domain are strikingly similar for the two models, in most months. Relative humidity changes also follow changes in precipitation to some degree. There are generally increases from February through June (on the order of 10%) and then decreases in July through October. In winter the CSIRO simulates slight decreases whereas the RegCM produces slight increases. Largest (about 20%) decreases occur in July and August in both models. Surface winds in general decrease (on the order of 10%) in both models in most months, but slightly larger decreases are found in the RegCM.

5. Signal-to-Noise Considerations

In this section we discuss two issues which are important for determining the robustness of the two different scenarios and whether they are truly different. One issue is the fact that only five years were used from the 30 year runs of the CSIRO to serve as boundary conditions for the RegCM. This is a relatively short time series, and certainly a more robust scenario could have been developed from using all 30 years of the CSIRO. This issue considers how representative the particular five years we used were in relation to the full 30 years of the CSIRO. A second issue is the signal-to-noise problem in determining how different the coarse scale and fine scale scenarios are from each other. Here the issue of sample size is also important. When these runs were initially produced for the long term agriculture project, limitations in computer time allocation prohibited us from producing longer runs. We demonstrate below how this affects the two issues.

5.1. THE FIVE YEARS OF CSIRO IN RELATION TO THE FULL RUN LENGTH

We compared the particular five years of control and $2 \times CO_2$ runs of the CSIRO we used with longer time periods to situate the particular five years of the climate scenarios (i.e., ratios or differences) in the context of the longer time series. In general we found that the longer the simulation, the smoother the seasonal cycle of the ratios ($2 \times CO_2$/control) for precipitation (Figure 7). The five year simulations show greater variability of the seasonal cycle of the ratios (Figure 7), but the over all shape of the seasonal cycles are similar regardless of run length. This tendency was found at all grids. In this instance, in certain months, such as March, the ratios decrease with run length, but this is not uniformly the case. There are similarities in the ratios regardless of run length through the summer months, when decreases in precipiitation are found. The shortest run length does not have the most extreme ratio during these months, which are particularly important from the point of the crop model responses. Interestingly enough, at most grids the ratios in the spring months are higher for the five year segment than for the full 30 years, but ratios are very similar regardless of run length in the summer. From the point of view of agriculture, our 5-year CSIRO scenario likely is less draconian than the 30-year scenario, since the higher precipitation ratios (i.e., precipitation increases) in our scenario would result in less moisture stress in the spring, before the droughty summer months (when preciptation ratios are low), which occurs with all run lengths.

Using longer simulations of the CSIRO and then producing longer simulations of the RegCM thus would likely have produced different results than what we have produced here. Also, using a different five year period likely would have resulted in scenarios somewhat different from what we present here. However, since we are mainly interested in a sensitivity of the spatial scale effect of climate change scenarios, we are not overly constrained by this time slice problem. While a longer simulation would produce more robust results, and probably less extreme ratios in some months, our results are still useful as a sensitivity analysis. The difference between the five year ratios and 30 year ratios rarely resulted in different directions of change, but were generally a matter of degree.

Contrasts in the effect of run lengths for time periods within the full 30-year time series for temperature were much smaller than those for precipitation (Figure 8). At the same grid as in Figure 7, we see that the time series of control and doubled CO_2 for maximum summer temperature are highly stationary, resulting in little variation in the difference in the two time series with run length. The mean of the control run for the five years used in our scenario and the long-term mean was 31.5 °C, and the same for the $2 \times CO_2$ was 36.1 and 36.4 °C, respectively.

5.2. STATISTICAL COMPARISON OF THE FINAL SCENARIOS

Here we demonstrate that there are substantial differences in the final climate scenarios that serve as inputs to the crop models. We establish that the contrasts in the climate changes of CSIRO versus those of RegCM are statistically significant, and do not result from random noise. The only sensible way to do this, given the differences in the spatial scales of the scenarios, is to analyze the differences in the final scenarios, described in Section 4.3 above, that are produced on the same 50 km grid. These are the climate time series resulting from combining ratios and

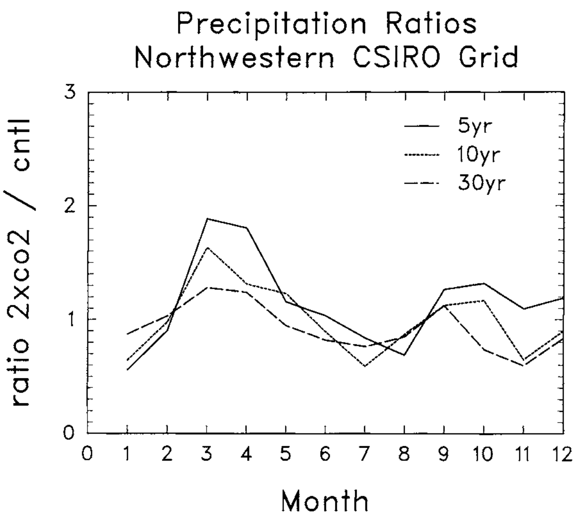

Figure 7. Ratios of precipitation 2 × CO_2/control for the CSIRO grid box in the northwestern part of the Southeast study area for time series of various lengths.

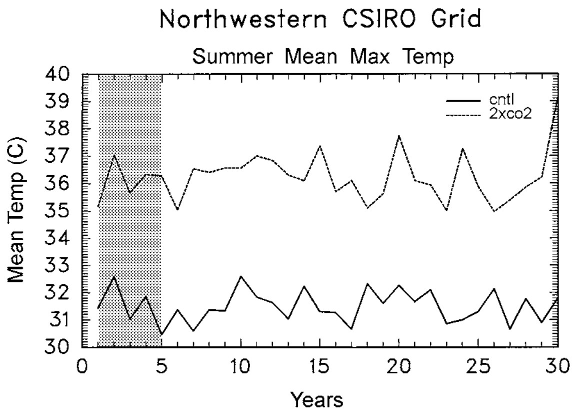

Figure 8. Thirty-year time series of summer mean maximum temperature from the CSIRO control and 2 × CO_2 runs, for the same grid box as in Figure 7 (northwestern part of the domain). Gray shading indicates the five years of the simulations used for the scenarios described in this paper.

differences with the observations. Each scenario contains 36 years of daily data at each 50 km grid point. We compared the final CSIRO scenario with the RegCM scenario applying the same statistical package used in Sections 3.2 and 4.2 above. We compared both the mean precipitation and mean temperatures. The most significant contrasts in the changed climate data sets for precipitation are in July (63% of grids are different at 0.05 level), August (60% significantly different, about 50% positive), September (33% significantly positive difference), and November (45% significantly negative, western part). Other months that have moderate amounts of significant differences are December (17% significant and negative); May (15%

significant and negative), March (13% significant mostly positive) and June (17% significant, mostly positive). In other months the areas of significant differences are under 10%. Temperatures are also significantly different in most months.

These results indicate that the differences in the changed climates produced as scenarios are substantial in many of the months important for agriculture in the Southeast. The fact that precipitation is substantially different in the summer months is particularly important. These results indicate that the contrasts in climate change from the two models are detectable as a signal. Even so, it must be emphasized that it is the total effect that the climate changes have on the crop models that ultimately matters. The crop models experience the complete integration of all the changes in the relevant variables for the entire year. Hence, establishing that the individual elements of the scenarios are statistically significantly different on a monthly basis is not the most crucial aspect of this study, from the point of view of impacts.

6. Summary and Conclusions

We have presented an analysis of equilibrium climate change experiments performed with a nested regional climate model over the southeastern United States and of the GCM experiments that provided the boundary conditions for the nesting. Our main conclusions can be summarized as follows:

1. Overall, in the control run the RegCM improved many aspects of the simulation compared to the driving CSIRO. In particular surface temperature and the spatial patterns of precipitation were better simulated in the regional model. The RegCM had a larger positive precipitation bias than the CSIRO in summer, which however was dominated by the contribution of a relatively small region.
2. The models reproduced the basic features of the climate of the region, but also showed significant deficiencies, most notably the failure to reproduce the spatial patterns of precipitation in the spring and fall, and a precipitation overestimation in summer. Minimum temperature was reproduced very well by the RegCM and overestimated by the CSIRO, while maximum temperature showed negative biases in both models, but these were smaller for the RegCM.
3. With doubled CO_2 forcing, both models simulated increases in temperature mainly between 4 and 5 °C, but larger increases were simulated for the spring minimum temperature by the CSIRO and for the summer maximum temperature by the RegCM. These changes are for the most part larger than the biases in both models, especially in the RegCM.
4. Both models simulated increases in precipitation in the spring, but these were larger for the CSIRO; and both models also simulated substantial decreases in summer precipitation, more so for the RegCM. These seasonal changes in precipitation were larger than the model biases in spring, but somewhat smaller than the biases in summer. The latter condition is common to other regional

modeling climate change experiments, particularly over the Southeast (Pan et al., 2001).

The fact that the RegCM overall enhances the reproduction of the regional climate compared to the CSIRO, increases the confidence that the response of the model to the increased CO_2 may be more realistic compared to the driving GCM. In any case, the differences in the climate changes simulated by the two models are substantial for some variables and seasons. The climate change simulated by the RegCM is for the most part a more severe climate change based on the changes in the summer. The spatial variability of the climatic changes are of course greater for the high resolution model.

These scenarios are employed as inputs to crop models in a number of the papers in this special issue, to determine whether the differences in the climate changes of the two models produce different changes in yields under climate change conditions. In this regard the scenarios serve as the first stage in a study to determine: (1) whether the spatial scale of climate scenarios matters when calculating changes in crop yield; and (2) whether these changes in crop yield produce substantially different economic impacts when employed in an agricultural economic model. Hence, the scenarios should be viewed in the context of a sensitivity study of the effects of spatial scale. While these scenarios thus should not be viewed as state-of-the-art scenarios of climate change, which would require the use of more recent projections from transient runs of AOGCMs, they are more than adequate for the purposes of this interdisciplinary project (Mearns, 2003).

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