RESPONSE OF SOYBEAN AND SORGHUM TO VARYING SPATIAL SCALES OF CLIMATE CHANGE SCENARIOS IN THE SOUTHEASTERN UNITED STATES

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Abstract. This study examines how uncertainty associated with the spatial scale of climate change scenarios influences estimates of soybean and sorghum yield response in the southeastern United States. We investigated response using coarse (300-km, CSIRO) and fine (50-km, RCM) scale climate change scenarios and considering climate changes alone, climate changes with CO_2 fertilization, and climate changes with CO_2 fertilization and adaptation. Relative to yields simulated under a current, control climate scenario, domain-wide soybean yield decreased by 49% with the coarse-scale climate change scenario alone, and by 26% with consideration for CO_2 fertilization. By contrast, the fine-scale climate change scenario generally exhibited higher temperatures and lower precipitation in the summer months resulting in greater yield decreases (69% for climate change alone and 54% with CO_2 fertilization). Changing planting date and shifting cultivars mitigated impacts, but yield still decreased by 8% and 18% respectively for the coarse and fine climate change scenarios. The results were similar for sorghum. Yield decreased by 51%, 42%, and 15% in response to fine-scale climate change alone, CO_2 fertilization, and adaptation cases, respectively – significantly worse than with the coarse-scale (CSIRO) scenarios. Adaptation strategies tempered the impacts of moisture and temperature stress during pod-fill and grain-fill periods and also differed with respect to the scale of the climate change scenario.

1. Introduction

Increasing concentrations of greenhouse gases in the atmosphere will likely alter global temperature and precipitation patterns during the next century (Houghton et al., 2001). The agricultural impacts of such changes would depend on the magnitude and spatial expression of change, and farmers' ability to adapt. Agriculture in the southeastern United States could be particularly vulnerable to climatic change: current summer maximum temperatures in the region often exceed 32 °C, evaporation rates exceed growing season precipitation, and agricultural soils typically have relatively low water-holding capacity and low fertility. Moreover, the profitability of farming in the Southeast depends on relatively low capital inputs, thus limiting some options for mitigating the impacts of climate change.

Some of the uncertainty surrounding estimates of regional agricultural response to future climate change comes from the tools used to measure crop response to environmental change. The influence of climate change on crop yield has been

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estimated with a variety of crop models that differ with respect to complexity and the degree to which they incorporate physiological processes (Boote et al., 1996). Some studies have demonstrated that different crop models produce different yield response to the same climate conditions (Xie et al., 2001; Wolf, 2002a). Others have examined the influence of varying soil type (Wassenaar et al., 1999), carbon dioxide level (Brown et al., 2000; Haskett et al., 2000), or field management, including adaptation strategies related to planting date, cultivar, fertilization, and irrigation (Curry et al., 1990; Rosenzweig and Iglesias, 1998; Alexandrov and Hoogenboom, 2000; Tubiello et al., 2000; Wolf, 2002b).

Climate change scenarios and the means by which they are incorporated into crop simulation models present another uncertainty in agricultural impact studies. Researchers generally recognize such uncertainties and adjust for them in a variety of ways. For example, it is widely recognized that GCMs were not designed to make projections at a regional scale. Therefore, many impact studies have used output from more than one GCM to create a range of possible scenarios, expressing the uncertainty associated with regional-scale projections (e.g., Curry et al., 1995; Alexandrov and Hoogenboom, 2000). It is also clear that GCM grids are coarse relative to the scale for which crop simulation models were developed. Researchers have accommodated these scale differences by downscaling GCM output to individual simulation sites. The latter approach has been accomplished statistically (Semenov and Barrow, 1997) and by interpolation from the GCM grid points to smooth changes spatially (Alexandrov and Hoogenboom, 2000). Some have created a physically-based climate change scenario by nesting relatively finer scale regional climate models within a GCM (Easterling et al., 2001; Guerena et al., 2001; Mearns et al., 2001). Preliminary evidence from these studies suggests that the spatial scale of the climate change scenario influences the magnitude and spatial patterns of agricultural impacts. Here we investigate that premise further.

We examine the potential impacts of climate change on soybean and sorghum yield in the Southeast United States using two scenarios of climate change that differ in spatial resolution. A coarse scenario is produced from GCM output, while a fine scenario is produced by nesting a regional climate model within the GCM. This allows us to compare crop response relative to the scale at which we express climate change. We consider these differences with respect to crop development and stress, and examine how a wide range of adjustments could mitigate yield decreases resulting from climate change. Section 2 discusses the crop models and climate change scenarios used, and outlines the simulation experiments. We present and interpret our results in Section 3 and make summary remarks in Section 4.

2. Methods and Data

2.1. CROP MODELS

We simulated soybean and sorghum yield in 414 50-km grid cells across the Southeast using the CROPGRO-Soybean and CERES-Sorghum v. 3.1 crop simulation models which are part of the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) suite of crop simulation tools (Tsuji et al., 1994). These models simulate carbon, water, and nitrogen balances for the plant and soil (Hoogenboom et al., 1994; Boote et al., 1998). They have been used extensively in climate impact studies because their structure links plant processes to environmental and management inputs. CROPGRO-Soybean has been validated across a range of different environmental conditions and has shown skill in predicting phenological stages, biomass accumulation, and yield (Brisson et al., 1989; Colson et al., 1995; Kiniry et al., 1997; Boote et al., 1997; Carbone et al., 2003). CERES-Sorghum has also been calibrated and tested in diverse environments (Birch et al., 1990; Robertson et al., 1993; Hammer and Muchow, 1994; Castrignano et al., 1997).

While physiologically based, the IBSNAT crop simulation models require inputs that are either readily available or can be adequately estimated. These include meteorological inputs such as daily solar radiation, maximum and minimum temperatures, and precipitation. We acquired daily maximum and minimum temperatures, and precipitation from the National Weather Service cooperative network. Solar radiation was estimated stochastically using the synthetic weather generator, WXGEN (Richardson and Nicks, 1990). Mearns et al. (2003a, this issue) provide further details on the creation of the baseline climate data set. The crop models also require the following soils information: lower limit of plant-extractable soil water, drained upper limit soil water content, and saturated water content for each soil layer. We estimated values for these variables empirically, using a regression model relating soil texture characteristics to field capacity and wilting point (Baumer et al., 1994). Soil texture properties from one soil in each 50-km grid was selected from the State Soil Geographic (STATSGO) data base (Reybold and TeSelle, 1989). We considered only ‘prime farmland’ soils and selected the agricultural soil type that occupied the greatest area of each grid. While the soils differ between grid cells, some general spatial patterns exist across the region. Sands and loamy sands cover most of the Atlantic Coastal Plain, sandy loams dominate areas further inland (in the Piedmont), and silt loams cover most of the western portion of the study region, including the Mississippi Delta. The models also need field management inputs, including cultivar, sowing date, plant population, row spacing, sowing depth, and irrigation scheduling. A series of cultivar coefficients express the duration of growth stages, maximum growth rates, photoperiod, threshold temperatures, and grain or seed characteristics (Table I).

Table I

Soybean genotype coefficients for CROPGRO-Soybean simulations

Maturity	CSDL	PPSEN	EM–FL	FL–SH	FL–SD	SD–PM	FL–LF
I	13.84	0.203	17.0	6.0	13.0	32.0	26.0
IV	13.09	0.294	19.4	7.0	15.0	34.5	26.0
V	12.83	0.303	19.8	8.0	15.5	35.0	18.0
VII	12.33	0.320	20.8	10.0	16.0	36.0	18.0

CSDL: Critical short day length below which reproductive development progresses with no daylength effect (hours).
PPSEN: Slope of the relative response of development to photoperiod with time ($hour^{-1}$).
EM-FL: Time between plant emergence and flower appearance (photothermal days).
FL-SH: Time between first flower and first pod (photothermal days).
FL-SD: Time between first flower and first seed (photothermal days).
SD-PM: Time between first seed and physiological maturity (photothermal days).
FL-LF: Time between first flower and end of leaf expansion (photothermal days).

In the initial baseline and climate change crop simulations, we used one uniform planting date (calendar day 150 – approximately May 30) and cultivar across the entire region. We used published values for soybean coefficients from the generic maturity group V and sorghum coefficients from Cargill 837 (Tsuji et al., 1994). While planting date and variety vary over the study period and region, this strategy allowed us to control for these management variables and focus on the impacts of climate change. We consulted National Agricultural Statistics Service (USDA, 1997) and state agricultural extension reports, and county agricultural extension agents to select one planting date and cultivar without straying far from historic and current management practices. The impact of this strategy was minor as discussed in the adaptation results below. For all simulations, the CROPGRO model was run with water balance, soil-N balance, and plant-N balance options turned on. The Priestley-Taylor method (Priestley and Taylor, 1972) was used to compute crop potential evapotranspiration. The model was run in 'sequence mode' through consecutive years in order to preserve soil moisture values from one season to the next. We simulated yield in every grid cell in the entire region. While agricultural statistics show variability in production across the Southeast, every southeastern state produces at least some soybean and sorghum, and climatic change could allow production in areas not currently used.

We simulated baseline soybean and sorghum yields for the 36-year period, 1960–1995 using observed daily meteorological data from the National Weather Service cooperative network. One station was selected to represent each of the regional climate model 50-km grids on the basis of proximity to the grid center and data quality (see Mearns et al., 2003a). Then we reran the models for three cases: (1) climate change only; (2) climate change plus direct CO_2 fertilization effects –

referred hereafter as the 'elevated-CO_2 case'; and (3) the elevated-CO_2 case with adaptation. We used an ambient CO_2 value of 330 ppm for the baseline and climate change only cases, and 540 ppm for the elevated-CO_2 cases. CROPGRO-Soybean and CERES-Sorghum consider the effects of CO_2 fertilization by adjusting photosynthesis and leaf stomatal resistance in response to ambient CO_2 concentrations (Boote and Pickering, 1994; Pickering et al., 1995). Pickering et al. (1995) reported modeled photosynthesis increases of 30% and potential evapotranspiration decreases of 5% in response to a doubling of ambient CO_2. We performed simulations for control and climate change scenarios using both dryland and irrigated options. While we will report primarily on dryland simulations, the irrigated runs provide a standard to investigate the influence of water stress.

2.2. CLIMATE CHANGE SCENARIOS

Climate change scenarios for the southeastern United States were constructed at two different spatial resolutions. Controlled and doubled CO_2 equilibrium experiments of the Australian CSIRO Mk2 GCM (Watterson, 1998; Watterson et al., 1999) were used to generate a coarse resolution (approximately 3.2° latitude × 5.6° longitude) scenario with 11 grid boxes across the Southeast. A nested regional climate model (RCM), driven by the CSIRO boundary conditions, was used to create a fine resolution (50-km) scenario for 414 grid boxes across the region. The general features of the two scenarios are similar, but important differences often exist at the subregional scale (Giorgi et al., 1998; Mearns et al., 2003a). For example, the CSIRO model predicts greatest June, August, and September temperature increases in the western portion of the study region, while June–September RCM temperature increases are highest near the Atlantic. While both models simulate increases in summer temperature, the RCM increases are greater. CSIRO simulates increases in June precipitation for most of the Southeast, whereas RCM simulates mainly decreases. Both models simulate precipitation decreases during July, August, and September, but the decreases are more severe for the RCM, especially along the Atlantic Coastal Plain and Piedmont. Temperature and precipitation changes from RCM are more spatially variable than those produced by CSIRO. Mearns et al. (2003a) provide further details on the climate change scenarios.

Output from CSIRO and RCM, representing climate change with CO_2 doubling, was used to adjust the maximum and minimum temperature, precipitation, and solar radiation of a 36-year (1960–1995) observed climate data set. Observed data from one station within each 50-km RCM grid were used. In the coarse-resolution scenario, monthly mean temperature differences ($2 \times CO_2$ – baseline) or precipitation ratios ($2 \times CO_2$/baseline) from the CSIRO model were imposed uniformly on all 50 km grids encompassed within each CSIRO grid. The high-resolution scenario was created by imposing the regional model changes uniquely on observations in each 50-km grid.

To provide input for an agricultural economic model of the U.S., simulations were also run for stations elsewhere in the United States to account for simultaneous climate change impacts outside the Southeast. We used observed data from selected stations from the period 1961–1985 to simulate baseline yield in other important soybean- and sorghum-growing regions. Climate change scenarios were created for these other stations using the same GCM results and additional runs with the same RCM in other areas of the U.S. We measured the impacts of climate change at these other stations by comparing baseline yield against the two climate change scenarios. Yield changes for these other regions are also discussed in Mearns et al. (2003b). The results were incorporated into the Agricultural Sector Model (ASM; see Adams et al., 2003).

2.3. ADAPTATION CASES

In an additional series of simulations, we adjusted planting date and cultivar characteristics – two adaptation strategies that growers could use to mitigate the impacts of climate change. For soybean, we simulated yield using four different maturity groups (I, IV, V, and VII), each with eight planting dates (calendar days 100, 110, 120, 130, 140, 150, 160, and 170). These adjustments were designed to alter growing season length and change the timing of phenological events relative to the most stressful part of the growing season. Table I outlines how crop coefficients vary among the four cultivars. For sorghum, we adjusted crop growth parameters to shorten the juvenile and grain-filling stages, and moved the planting date from calendar day 150 to calendar day 100 to avoid the hottest part of the summer. For both crops, we determined the combination of cultivar and planting date that produced the highest 36-year average yield at both the grid cell and state-wide level and used this yield value to measure the impacts of climatic change with adaptation. Table II summarizes all cases.

2.4. MEASURING YIELD RESPONSE

We calculated the 36-year average yield for all 50-km grid cells for the three cases and two climate change scenarios. Percentage yield change (from the baseline simulation) for each was calculated as:

$$\Delta Y = \frac{Y - Y_b}{Y_b},$$

where Y = average simulated yield using one of the six cases specified in Table II and Y_b = baseline yield (36-year average yield using the observed 1960–1995 climate record).

For each crop, we used linear modeling techniques to test the hypothesis that mean yields from all scenarios and cases were equal. If this hypothesis was rejected, we conducted pairwise comparisons to test whether selected pairs of cases produced significantly different mean yields. Since standard analysis of variance

Table II
Soybean simulation scenarios

Case	Climate change scenario	Ambient CO_2 available to crop (ppm)	Soybean		Sorghum	
			Planting date	Cultivar	Planting date	Cultivar
Baseline (B)	1960–1995 observed	330	150	Generic MG V	150	Cargill 837
CSIRO climate change only (C)	CSIRO	330	150	Generic MG V	150	Cargill 837
RCM climate change only (R)	RCM	330	150	Generic MG V	150	Cargill 837
CSIRO climate change and elevated CO_2 (C2)	CSIRO	540	150	Generic MG V	150	Cargill 837
RCM climate change and elevated CO_2 (R2)	RCM	540	150	Generic MG V	150	Cargill 837
CSIRO climate change and elevated CO_2 w/adaptation (C2a)	CSIRO	540	Optimal	Optimal	100	Shortened juvenile and grain-fill periods
RCM climate change and elevated CO_2 w/adaptation (R2a)	RCM	540	Optimal	Optimal	100	Shortened juvenile and grain-fill periods

(ANOVA) methods require independent sample data, and simulated yields are correlated in both space and time, we used a mixed models approach (Littel et al., 1996) to account for spatial and temporal autocorrelation. We conducted separate analyses to determine which climate variables contributed most to differences between soybean yields simulated with the CSIRO and RCM scenarios. This included eight CSIRO grids that comprise approximately 95% of the study area. For each CSIRO grid, yield differences were regressed on climate variable differences during the growing season. Finally, we examined yield changes with regard to temperature and moisture stress during important physiological stages.

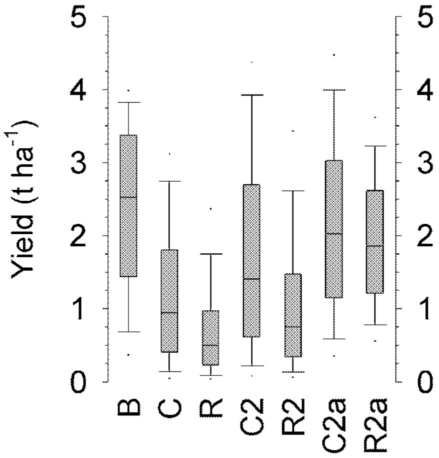

Figure 1. Dryland simulated soybean yield for each climate scenario and case. Table II describes each case. In this figure, and all other box plots, the outer dots represent the 5th and 95th percentiles, the whiskers represent the 10th and 90th percentiles, the edges of the box represent the 25th and 75th percentiles, and the central line represents the median.

3. Results and Discussion

3.1. SOYBEAN

Southeast dryland soybean yield, simulated with the 1960–1995 control climate, averaged 2.38 t ha^{-1}. This baseline value closely approximates observed yields during this period. A few grids at the higher elevations of the southern Appalachians, had low average yield because of below-optimal temperatures and occasional freezes during the growing season.

Both CSIRO and RCM climate change scenarios led to large regional soybean yield decreases. Southeast mean yield dropped by 49% (CSIRO) and 69% (RCM) when considering climate change alone (Figure 1). The decreases were not uniformly distributed. For the CSIRO scenario, they were worst in Arkansas, northern portions of Louisiana, Mississippi, and Alabama, and across the Piedmont portions of Georgia and the Carolinas. Yield decreases exceeded 60% in these areas and were smaller along the Gulf and Atlantic coasts. ANOVA results show that yield was significantly ($\alpha = 0.01$) lower than baseline yield in all southeastern states. Curry et al. (1990) reported comparable yield decreases using climate change scenarios of similar magnitude.

Mean yield decreases were tempered by incorporating the direct effects of CO_2 fertilization. The regional average yield was 26% (CSIRO) and 54% (RCM) lower than baseline yield. Yield losses varied regionally. In the CSIRO scenario with elevated CO_2, soybean yield decreased by more than 80% in portions of Arkansas and Louisiana and more than 40% across a broad region extending across northern Mississippi and Alabama, and the Piedmont portions of Georgia, and the Carolinas.

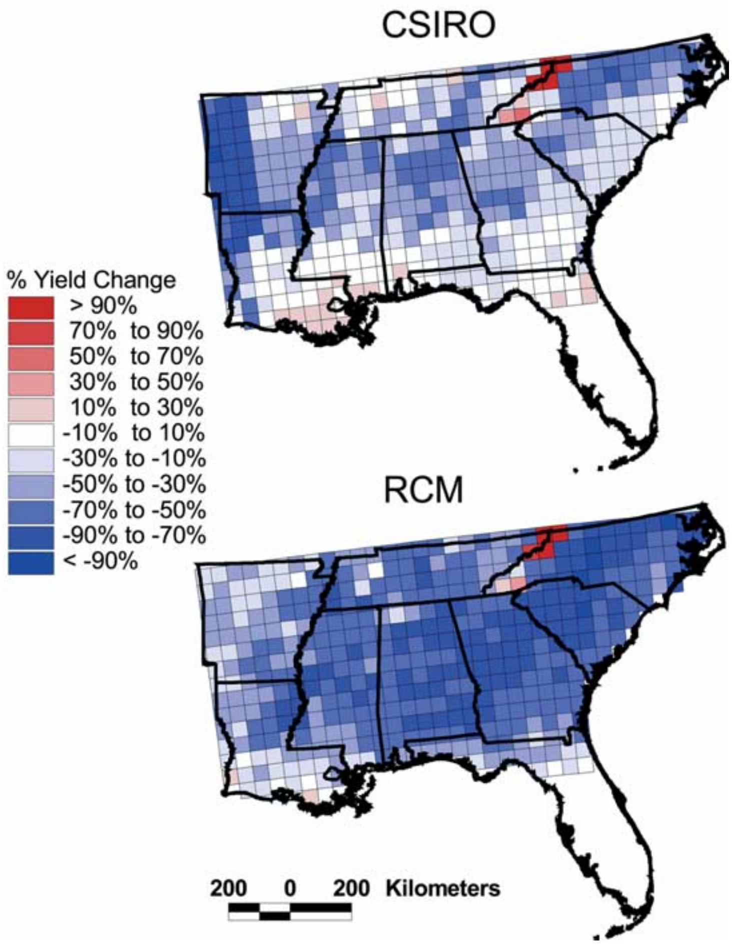

Figure 2. Percentage dryland simulated soybean yield change for climate change with elevated CO_2 for CSIRO and RCM climate change scenarios.

The worst yield reductions associated with the RCM scenario are found in the same Piedmont region as well as Alabama and parts of Mississippi and Louisiana near the Mississippi River (Figure 2). ANOVA results show that these yield decreases are statistically significant ($\alpha = 0.01$) in all southeastern states.

Table III summarizes yield response to climatic change at the state level – the scale used in the agricultural sector model (see Adams et al., 2003). The trend and magnitude of yield response to each scenario reflect the spatial patterns described above. The coefficient of variation reported in the table measures how state-averaged yield varied over the 36-year simulation period for each scenario. Several conclusions can be drawn from these data: (1) Without adaptation, the CSIRO and RCM climate change scenarios cause significant increases in inter-annual yield variability. (2) Direct CO_2 effects don't influence yield variability.

Table III

State-level dryland soybean yield changes for each scenario

State	Baseline (B)		% Change from baseline soybean yield and 36-year coefficient of variation											
			CSIRO 330 (C)		RegCM 330 (R)		CSIRO 540 (C2)		RegCM 540 (R2)		CSIRO 540 + a (C2a)		RegCM 540 + a (R2a)	
	Yield ($t\ ha^{-1}$)	CV	% Δ	CV	% Δ	CV	% Δ	CV	% Δ	CV	% Δ	CV	% Δ	CV
AL	2.21	28.2	−53.4	41.2	−77.7	45.8	−30.3	41.3	−66.1	47.2	−15.6	36.9	−18.8	22.2
AR	1.79	36.8	−66.4	50.6	−61.1	49.3	−51.3	50.3	−42.6	49.7	+6.9[a]	24.4	+13.4	19.6
FL	2.55	13.7	−35.4	27.1	−55.3	35.1	−3.8	27.2	−33.3	34.9	+2.4	25.3	−8.5	22.8
GA	2.34	24.7	−50.5	38.8	−78.6	41.2	−27.0	38.7	−68.1	41.3	−16.4	37.6	−33.6	23.6
LA	2.40	18.8	−42.4	28.6	−52.2	37.1	−16.8	27.5	−29.3	35.6	−1.7[a]	24.5	−1.7	26.8
MS	2.47	21.2	−47.4	36.4	−71.6	49.6	−23.9	36.0	−57.8	49.8	−7.9	36.4	−15.9	30.3
NC	2.69	18.0	−51.0	32.9	−73.7	35.2	−28.6	32.7	−61.6	35.4	−15.2	26.2	−39.5	25.8
SC	2.71	22.8	−52.1	42.2	−81.6	45.5	−30.3	42.2	−73.5	47.6	−17.6	37.4	−43.6	28.7
TN	2.60	22.9	−43.4	42.3	−66.8	55.1	−17.7	40.2	−49.9	53.1	+1.0	16.7	−12.4	19.6
Domain	2.38	19.1	−49.4	31.2	−69.2	35.8	−26.1	30.8	−54.3	25.7	−7.6	19.7	−18.3	17.8

[a] Indicates that yields are NOT significantly different ($\alpha = 0.05$).

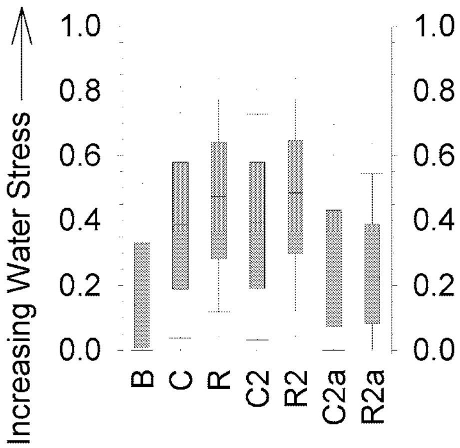

Figure 3. Soybean pod-fill water stress for each scenario and case. Growth rates are reduced linearly with increasing moisture stress from 0 (no stress) to 1 (complete stress).

There was essentially no difference in the yield results between climate change alone and climate changes with CO_2 fertilization. (3) Adaptation strategies (discussed below) generally reduced variability. For the CSIRO scenarios, variability modestly decreased in most states, but significantly decreased in Arkansas and Tennessee. For the RCM scenarios, variability significantly decreased in all states. While interannual yield variability in some states was higher for the adaptation cases than the baseline climate, it was the same or lower in many states.

The spatial pattern of yield decrease related closely to the greatest changes in maximum temperature and precipitation. These two variables combine to cause higher water stress during the pod-fill period in nearly every grid cell and year. Water stress during pod-fill significantly influences subsequent soybean yield (Haskett et al., 2000). CROPGRO-Soybean reduces photosynthesis and growth rates linearly as a function of computed water stress. Water stress during pod-fill is significantly higher for each of the climate change scenarios (Figure 3). It was associated with 44–68% of the simulated yield variance depending on scenario. Interestingly, CO_2 fertilization did not affect water stress. CO_2 enrichment increased leaf area index and, therefore, photosynthetic production. However, evapotranspiration remained essentially the same for the climate change only and elevated CO_2 scenarios because model adjustments for stomatal closure at higher CO_2 levels offset the influence of greater leaf area. When CO_2 was increased to 540 ppm, average plant biomass and yield increased by at least 20% in every grid cell. Consequently, water use efficiency, defined as either biomass or yield divided by evapotranspiration, increased for both climate change scenarios (Figure 4). This finding is consistent with Phillips et al. (1996).

Water stress during reproductive stages did not explain all low yields. In some cases, it was related to high temperatures during reproductive stages. CROPGRO-Soybean optimizes development rate (including processes related to photosynthetic

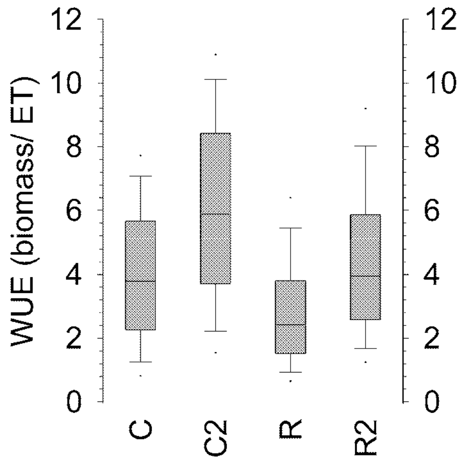

Figure 4. Soybean water use efficiency (WUE) as a function of CO_2 fertilization for CSIRO and RCM scenerios. WUE is measured as biomass or yield divided by evapotranspiration.

growth, node formation, seed growth, pod addition, and partition to pods) when hourly temperatures range between 22 and 34 °C, and it reduces these processes linearly at temperatures below and above these values (Boote et al., 1998). While it is impractical to reconstruct hourly temperature for each grid cell and growing season, several summary variables (e.g., average bloom or pod-fill temperature) can be used to identify periods of potential temperature stress that explain yield decrease. Average bloom-period maximum temperatures were nearly always lower than 34 °C in the baseline scenario, and usually exceeded 34 °C for the two climatic change scenarios (Figure 5). While average maximum temperature during bloom serves only as a proxy for modeled temperature stress, the relationship between this variable and final yield approximates the model function linking temperature to development rate (Boote et al., 1998). As average bloom-period maximum temperature increases (from the baseline, to CSIRO, to RCM scenarios) fewer and fewer cases fall within the optimum temperature range, and yield drops significantly. We also found that yield dropped when average pod-fill maximum temperature exceeded certain thresholds. In the RCM scenario, when yield fell below 1.00 t ha^{-1} with *low* water stress, it was often because pod-fill temperature exceeded 38 °C (Figure 6). These results echo the findings of Ferris et al. (1998) whose greenhouse experiments showed reductions in photosynthetic rate at high temperatures. Results from irrigated simulations further support the argument that high reproductive-stage temperatures suppress yield. In these simulations moisture stress was eliminated. Yield increased in nearly every grid, but percentage change varied as a function of maximum temperature. The greatest increases occur in the coolest regions, and the smallest increases occur in areas with the greatest maximum temperature changes. Regression analysis, designed to show differences between CSIRO and RCM soybean yields, reinforced many of the explanations

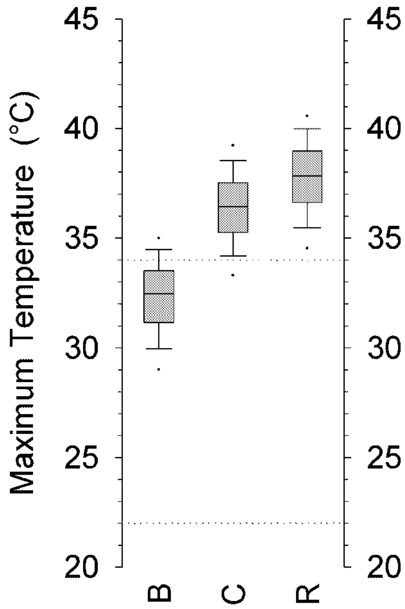

Figure 5. Soybean average bloom-period maximum temperature for each climate scenario.

above. July, August, and September precipitation, and August and September maximum and minimum temperature were the most consistent predictor variables accounting for yield differences between the CSIRO and RCM scenarios.

The very high temperatures during reproductive stages in the climate change scenarios also extended the average growing season length (defined as the period from germination to physiological maturity). This counter-intuitive result contrasts with some previous work (e.g., Alexandrov and Hoogenboom, 2000) showing that warmer temperatures hasten both vegetative and reproductive stages, thereby shortening the growing season. In our climate change scenarios, we find that growing season gets longer where temperature increases the most. For the CSIRO scenario, this occurs predominantly in the western part of the study area, while in the RCM scenario it is most pronounced in the eastern portions. Growing season was shortened only along the northern edge of the study region and at high elevations where baseline climate temperatures were below the optimal range for photosynthetic growth and, therefore, benefitted from the temperature increase imposed by the CSIRO and RCM scenarios. This point is illustrated by the relationship between growing season length and average maximum temperature during the bloom period (Figure 7). Below about 34 °C, growing season length generally decreases with increasing maximum temperatures during the bloom period. At temperatures higher than 34 °C, growing season length generally increases with increasing temperature. Average maximum temperature during most bloom periods in the baseline scenario are lower than 34 °C, but are higher than 34 °C in the CSIRO and RCM scenarios. These findings relate directly to the method by which CROPGRO-Soybean calcu-

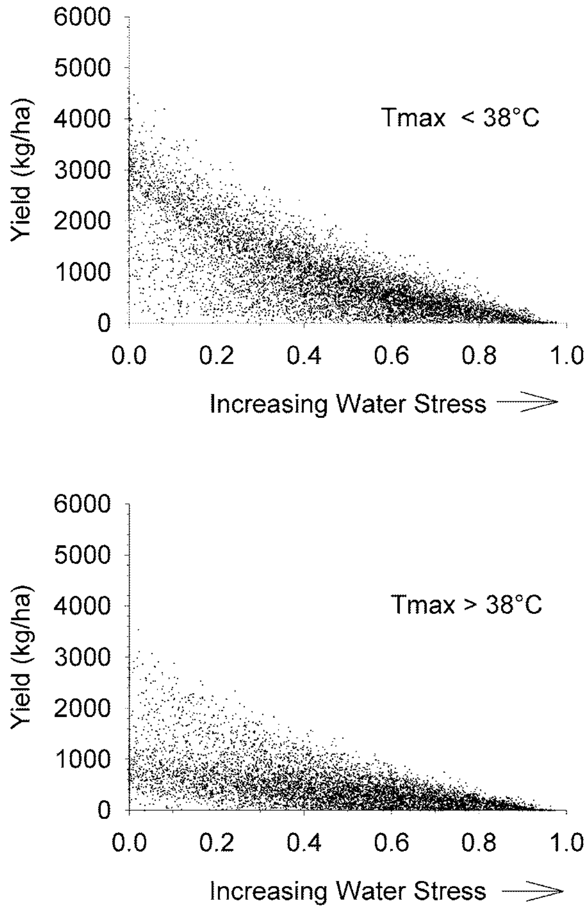

Figure 6. The relationship between pod-fill water stress and yield for the RCM, elevated CO_2 case and its dependence on temperature. Cases are separated on the basis of average pod-fill period maximum temperatures above or below 38 °C.

lates physiological development rates. Development in each stage is determined by sensitivity to temperature, photoperiod, and water and nitrogen stresses. Under optimal conditions for these variables, one physiological day is accumulated for each calendar day (Boote et al., 1989, 1998). Less than one physiological day was accumulated on every calendar day when temperature exceeded optimal conditions. Peart et al. (1989) and Curry et al. (1990) reported similar model behavior with high temperatures during reproductive stages. These findings, and the model structure itself, are further supported by both theoretical (Boote et al., 1998) and empirical (Ferris et al., 1999) studies examining the relationship between temperature and development rate.

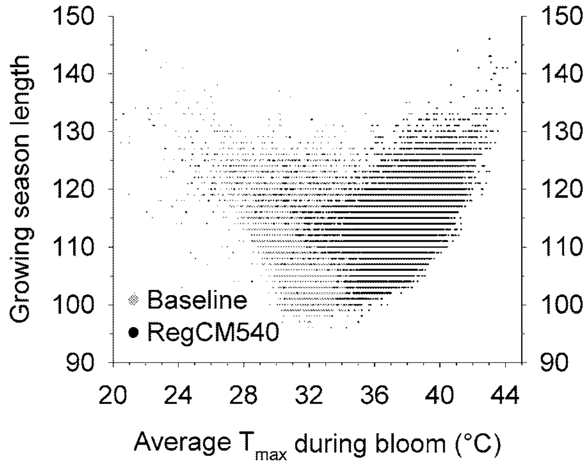

Figure 7. Growing season length vs. average bloom-period maximum temperature.

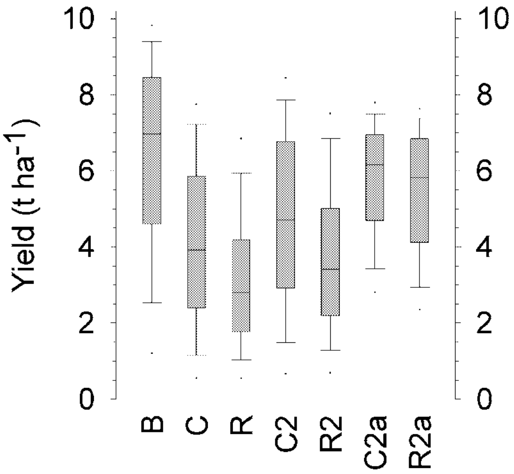

Figure 8. Dryland simulated sorghum yield for each climate scenario and case. Table II describes each case.

3.2. SORGHUM

Sorghum yield decreased significantly in response to the various climate change scenarios (Figure 8). In the climate change only cases, the CSIRO and RCM scenarios produced mean regional decreases of 36% and 51% respectively. Yield decreased from the baseline simulations in over 90% of all grid cells. As with soybean, interannual variability (measured by the coefficient of variation for state-averaged yield over the 36-year period) also increased in both climate change scenarios without adaptation (Table IV).

The spatial pattern of yield decreases closely matched that for soybean as both crops were influenced by the CSIRO and RCM patterns of maximum temperature

Table IV

State-level dryland sorghum yield changes for each scenario

State	Baseline (B)		% Change from baseline sorghum yield and 36-year coefficient of variation											
	Yield ($t\ ha^{-1}$)	CV	CSIRO 330 (C)		RegCM 330 (R)		CSIRO 540 (C2)		RegCM 540 (R2)		CSIRO 540 + a (C2a)		RegCM 540 + a (R2a)	
			% Δ	CV	% Δ	CV	% Δ	CV	% Δ	CV	% Δ	CV	% Δ	CV
AL	6.36	22.8	–40.2	27.2	–61.4	29.2	–30.5	26.0	–54.1	28.2	–6.5	15.9	–6.4	16.2
AR	5.33	29.7	–55.1	33.6	–45.8	34.0	–45.0	31.9	–34.3	32.1	+1.1 [a]	21.2	+5.1 [a]	18.7
FL	7.19	11.1	–24.8	16.3	–37.4	20.0	–17.0	14.2	–29.7	18.7	–16.4	15.0	–15.7	12.2
GA	6.62	17.8	–36.5	26.3	–60.9	25.0	–26.6	24.5	–53.3	23.5	–15.0	22.5	–25.4	26.2
LA	6.53	15.9	–35.0	18.1	–35.8	20.0	–27.3	16.4	–27.0	18.0	–18.4	16.5	–11.8	13.6
MS	6.94	19.0	–38.8	25.9	–55.5	31.6	–29.5	23.5	–46.8	30.1	–18.0	15.1	–12.0	13.7
NC	6.26	14.7	–28.0	22.7	–51.7	23.3	–15.9 [a]	21.0	–42.5	22.2	–3.9 [a]	18.8	–28.5	28.2
SC	7.52	14.1	–36.9	25.8	–63.3	25.4	–28.1	23.6	–56.9	24.7	–23.3	24.3	–43.0	31.7
TN	5.94	20.0	–22.5	28.6	–41.5	32.0	–6.9 [a]	24.9	–27.8	30.3	+9.3	13.6	–5.0 [a]	19.0
Domain	6.41	13.8	–35.9	20.5	–50.9	21.6	–25.7	18.9	–41.9	20.4	–9.9	13.7	–15.2	14.5

[a] Indicates that yields are NOT significantly different ($\alpha = 0.05$).

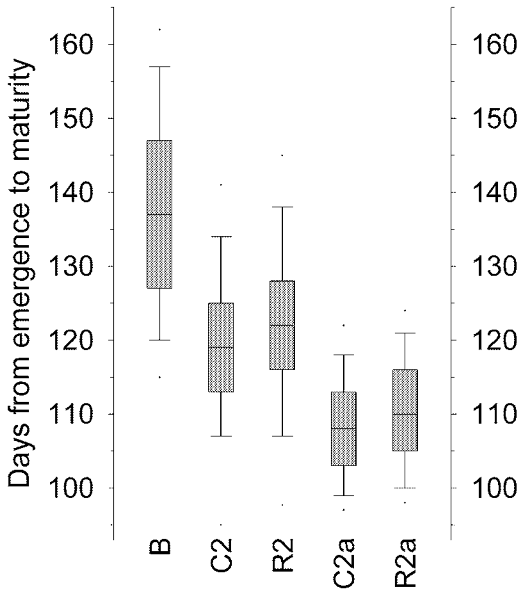

Figure 9. Sorghum growing season length for each climate scenario and case.

increases and precipitation decreases. The areas that fared best were the Gulf Coast, the north-central portion of the study region, and several Appalachian grids (where yield actually increased). The Gulf Coast had more modest temperature and precipitation changes than the rest of the Southeast. In the north-central and Appalachian grids, temperature increases had a less deleterious affect because baseline temperatures were lower than in other parts of the region. Regression analysis showed that July temperature and July and August precipitation were the most important predictor variables distinguishing the yield differences between CSIRO and RCM scenarios. The higher temperatures found in both the CSIRO and RCM scenarios shortened the grain-fill period and growing season by approximately 7 and 15 days, respectively (Figure 9). This finding was similar to that of Singh et al. (1998). When higher maximum temperatures were combined with lower precipitation, water stress also increased during the grain-fill period. Grain-fill water stress under the climate change cases was higher than the baseline case in nearly every year and grid cell (Figure 10).

Yield decreases were mitigated somewhat in the elevated-CO_2 cases, but not as dramatically as with soybean. This was expected, given that sorghum is a C_4 plant, and model adjustments relating ambient CO_2 concentration to photosynthetic rate differ between CERES-Sorghum and CROPGRO-Soybean accordingly. Nonetheless, CO_2 fertilization increased sorghum yield in nearly every year and grid cell (Figure 11). While an accelerated photosynthetic rate increased leaf area, stomatal resistance decreased in the simulation, limiting water losses. Consequently, water-use efficiency increased and grain-fill water stress was reduced in the elevated-CO_2

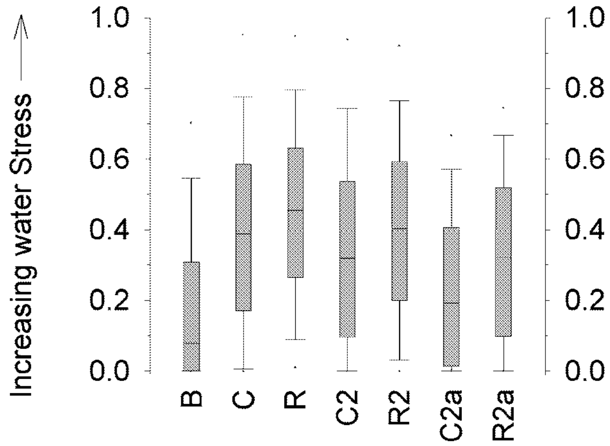

Figure 10. Sorghum grain-fill water stress for each scenario and case. Growth rates are reduced linearly with increasing moisture stress from 0 (no stress) to 1 (complete stress).

cases. This finding agrees with field studies of other C_4 species (Samarakoon and Gifford, 1996).

3.3. YIELD RESPONSE IN OTHER US REGIONS

We also simulated soybean and sorghum yield outside the Southeast using output from the same CSIRO simulations and RCM simulations for the western U.S. (Giorgi et al., 1998) and Great Lakes region (Bates et al., 1995). Output from these crop simulations was used in the agricultural sector model (ASM; see Adams et al., 2003) to measure net U.S. productivity in response to the two climate change scenarios. Soybean yield increased with the CSIRO and RCM climate changes projected in the Great Plains as precipitation increased during the spring and summer months. In the southern Great Lakes region, soybean yield generally increased, responding to the CSIRO increases in June and July precipitation, but decreased with the precipitation decreases of the RCM scenario. Sorghum yield increased in Nebraska and the Texas High Plains with the CSIRO scenario, but decreased in Kansas, Nebraska, Oklahoma, and the eastern half of Texas. These responses correspond closely with precipitation changes in June, July, and August. In the RCM scenario, precipitation increases caused modest sorghum yield increases across most of the Southern Plains. The only exception was in the Texas High Plains where RCM precipitation decreased, reducing yield. Given the importance of these soybean- and sorghum-growing regions, yield increases outside the Southeast influenced the results of the agricultural sector model.

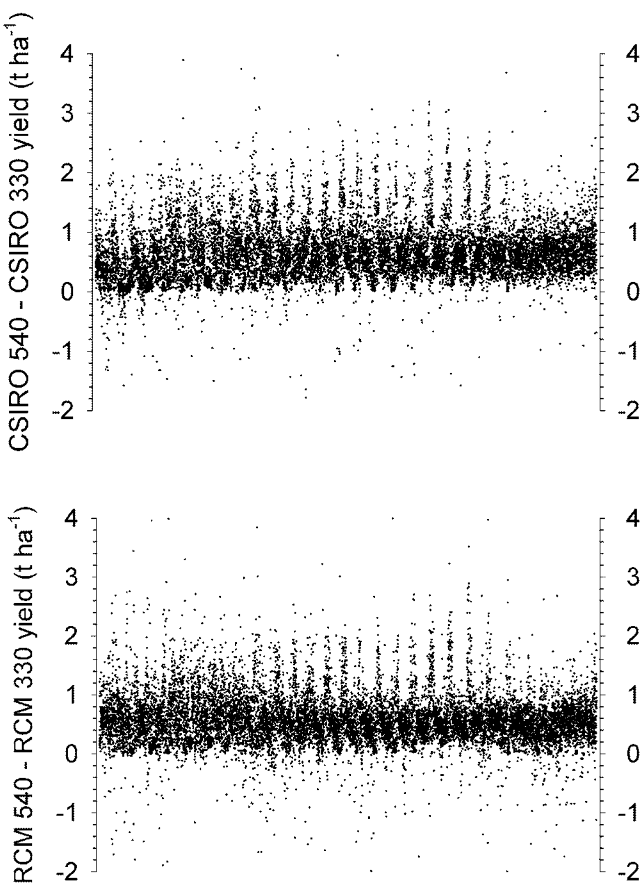

Figure 11. Sorghum yield differences between climate change only and climate change with elevated CO_2 for CSIRO and RCM climate change scenarios.

3.4. ADAPTATION CASES

3.4.1. *Soybean*

Adjusting planting date and cultivar significantly reduced the impact of climate change on simulated soybean yield. In the elevated-CSIRO case, average soybean yield increased from 1.76 t ha^{-1} to 2.20 t ha^{-1} when planting date and cultivar were altered in order to maximize state-level yield. Such adjustment produced higher yield than the baseline case in about half of the simulated years and grid cells, but because of extremely low yields in specific years and grid cells, domain-average yield was still 7.6% lower than the baseline case. Optimizing planting date and cultivar also improved yield response to the elevated RCM case. Simulated yield increased from 1.09 t ha^{-1} using the baseline planting date (calendar day 150) and cultivar (maturity group V), to 1.94 t ha^{-1} using dates and cultivars that optimized state-level yield. Given the more extreme temperature and precipitation changes of the RCM scenario, adaptation yield was higher than the baseline simulations in fewer than a third of all years and grid cells; regional average yield was still 18.3% lower than in the baseline simulations. Interannual variability also decreased in the adaptation levels such that it was approximately the same as the baseline scenario (Table III).

While optimal adjustments in planting date and maturity group varied spatially as a function of the intensity of each climate change scenario and soil type, two general strategies mitigated yield decreases due to climate change: planting lower maturity groups (I or IV) earlier in the season (mid-April) or planting higher maturity groups (V or VII) later in the season (mid-June). For the CSIRO scenarios, the former strategy improved yield in nearly half of all grid cells. It was particularly effective where the CSIRO-prescribed temperature and precipitation changes were greatest (Figure 12). In other regions, the highest yields resulted from the latter strategy – planting maturity group V or VII in mid-June. For the RCM scenarios, early planting with a low maturity group also reduced yield decreases. Seventy-five percent of all grid cells had the highest 36-year average yields using April 10 (calendar day 100) and maturity group (I or IV). Maturity group I worked best in the northern half of the domain, while maturity group IV dominated the southern half (Figure 12). Boote (1981) demonstrated that lower maturity groups could produce acceptable yield in the Southeast when planted early in the season. Yield in a number of grids benefitted from a shift to maturity group VII with a June planting date. This strategy worked best along the Coastal Plain of the Carolinas.

Two grid cells help to illustrate how planting and cultivar adaptations mitigate yield decreases associated with CSIRO and RCM climate change scenarios. One is located in Arkansas along the Mississippi River. The grid falls within a CSIRO cell where temperature increased between 3 and 6 °C from June through September, and precipitation decreased by 25–50% in July and August. The 36-year average CSIRO yield decreased by nearly 60% without adaptation. Planting maturity group IV earlier in the season (calendar day 100) provided one of the best adaptation strategies for this grid, as reduced pod-fill water stress and increased seed number and weight improved yield considerably. Despite the adjustments, the 36-year average was still 11% lower than the baseline yield. A second grid, located on the Coastal Plain of South Carolina, provides a less optimistic example. The projected RCM growing-season maximum temperature increase in this cell was over 8 °C; projected precipitation decreases ranged from 25 to 50%. Without adjustment, yield dropped by 70%. While no strategy could avoid the impacts of such changes, it is instructive to examine how early planting with a lower maturity group, or delayed planting with a higher maturity group, affected the timing of phenological stages relative to temperature. Figure 13 shows that the prolonged period of extreme temperatures would affect important growth stages for a wide range of adjustments. Planting quick-maturing varieties early, or slower-maturing varieties late in the growing season reduced heat and moisture stress, but yield was still 50% lower than in the baseline scenario. In this case, the RCM climate change

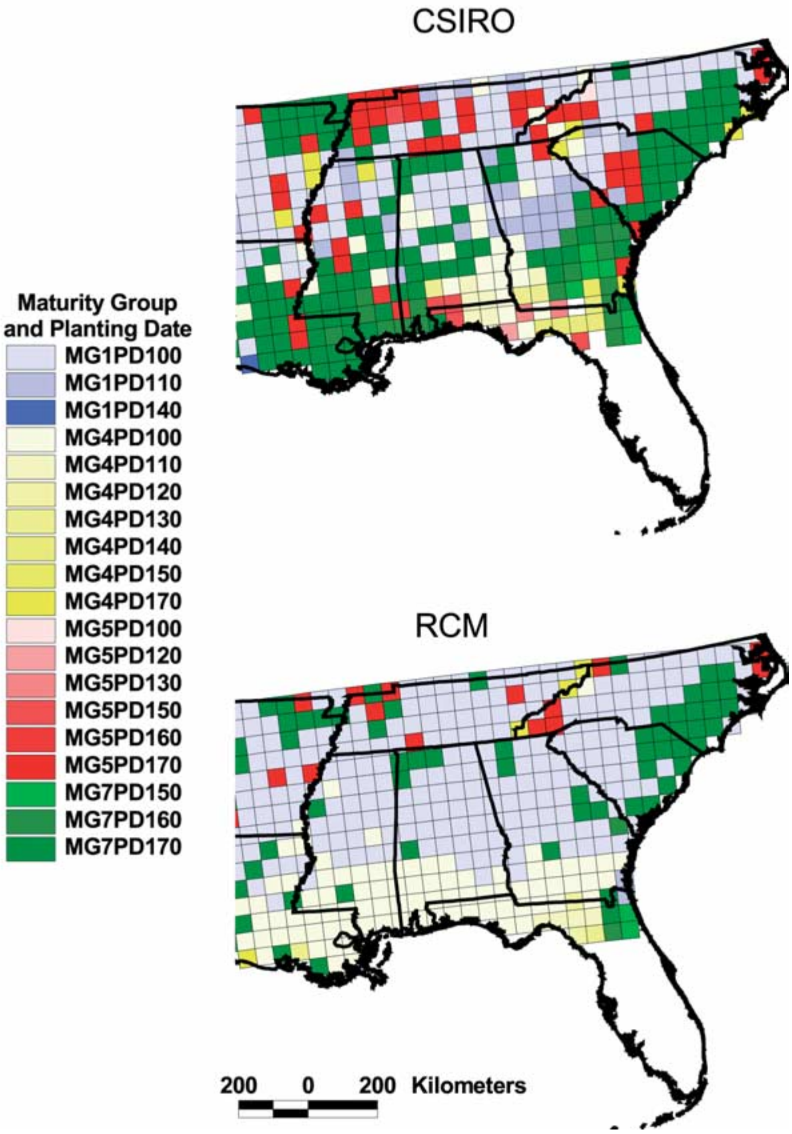

Figure 12. Optimal maturity group and planting date for the CSIRO and RCM climate change scenarios.

scenario presented extremes that the adaptation strategies considered here did not overcome.

3.4.2. *Sorghum*

Shortening the juvenile and grain-filling stages and advancing planting date reduced the impact of climate change on sorghum yield. In the elevated-CSIRO case, average yield increased from 4.76 t ha^{-1} to 5.78 t ha^{-1} when the thermal time of the

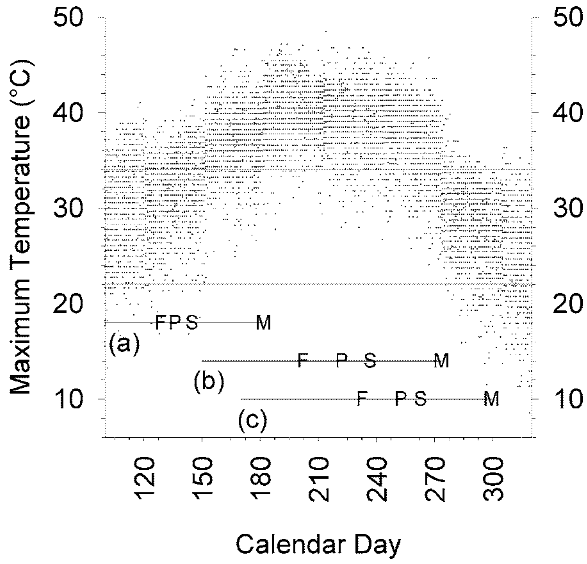

Figure 13. Maximum temperatures in the 36-year RCM time series for a 50-km grid in the South Carolina Coastal Plain. Dates of the first flower (F), pod (P), seed (S), and maturity (M) are shown for three adaptation strategies: (a) maturity group I, April 10 sowing; (b) maturity group V, May 20 sowing; and (c) maturity group VII, June 19 sowing.

juvenile stage was reduced by 100 degree days (base 8 °C) and planting date was shifted from May 30 to April 10. While these adjustments produced higher yield than the baseline case in about half of the simulated years and grid cells, average yield was still 9.9% lower than the baseline case. Optimizing planting date and cultivar also improved yield response to the elevated RCM case. Simulated yield increased from 3.73 t ha^{-1} to 5.44 t ha^{-1} with adjustments, but the Southeast average sorghum yield remained 15.2% lower than the baseline simulations. Equally important, our adaptation strategies decreased the interannual variability of yield such that it was comparable in magnitude to the baseline case. As with soybean, the adjustments to sorghum planting date and threshold thermal periods improved yield (Figure 8) by shifting the growing season to avoid water stress during grain fill (Figure 10). Unlike with soybean, however, the grain-fill period was shortened, reducing yield and countering some of the benefits of the adaptations.

4. Summary

This study examined how the spatial scale of climate change scenarios influences estimates of climate change impacts. Both the general circulation model and regional climate model used to create climate change scenarios for the southeastern United States projected temperature and precipitation changes that were associated with significant decreases in simulated soybean and sorghum yield. While consideration for direct CO_2 fertilization and for adjustments in planting date and cultivar mitigated yield decreases, regional averages remained lower than those simulated under baseline (1960–1995) conditions. Yield response to the projected climate changes was explained with respect to important physiological processes captured by the CROPGRO-Soybean and CERES-Sorghum models. Both crops were clearly influenced by water stress during important phenological stages (e.g., pod fill and grain fill). Successful adaptation strategies minimized water stress during these stages. Some of our results differ from other impact studies in the Southeast: for example, high maximum temperature slowed photosynthetic production and increased growing season length of soybean. This finding illustrates how certain thresholds, built into CROPGRO-Soybean, influence final yield in a manner consistent with other theoretical and empirical studies.

The spatial scale of climate change scenarios matters considerably. The magnitude and spatial patterns of yield response differed significantly between climate change scenarios. Again, such differences can be explained in the context of plant response to specific climate changes. The magnitude of temperature and precipitation projections varied between the CSIRO and RCM scenarios, producing different patterns of moisture stress in the two scenarios. Moreover, differences in the timing of temperature and precipitation change influenced yield response since soybean and sorghum showed sensitivity to water or temperature stress during particular growth stages. The influence of scale extends to adaptation strategies. In some cases, yield was maximized with dramatically different planting date and cultivar choices depending on climate change scenario. Our findings suggest that magnitude of uncertainty associated with the spatial scale of climate change projections warrants full consideration in climate impact studies.

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