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Carbon–Temperature–Water change analysis for peanut production under climate change: a prototype for the AgMIP Coordinated Climate-Crop Modeling Project (C3MP)

ALEX C. RUANE*, SONALI MCDERMID*†, CYNTHIA ROSENZWEIG*, GUILLERMO A. BAIGORRIA‡§, JAMES W. JONES¶, CONSUELO C. ROMERO‡ and L. DEWAYNE CECIL||

*Climate Impacts Group, NASA Goddard Institute for Space Studies, New York, NY, USA, †NASA Postdoctoral Program, Oak Ridge Associated Universities, Oak Ridge, TN, USA, ‡School of Natural Resources, University of Nebraska, Lincoln, NE, USA, §Department of Agronomy and Horticulture, University of Nebraska, Lincoln, NE, USA, ¶Agricultural and Biological Engineering Department, University of Florida, Gainesville, FL, USA, ||Global Science and Technology, Inc., Asheville, NC, USA

Abstract

Climate change is projected to push the limits of cropping systems and has the potential to disrupt the agricultural sector from local to global scales. This article introduces the Coordinated Climate-Crop Modeling Project (C3MP), an initiative of the Agricultural Model Intercomparison and Improvement Project (AgMIP) to engage a global network of crop modelers to explore the impacts of climate change via an investigation of crop responses to changes in carbon dioxide concentration ([CO_2]), temperature, and water. As a demonstration of the C3MP protocols and enabled analyses, we apply the Decision Support System for Agrotechnology Transfer (DSSAT) CROPGRO-Peanut crop model for Henry County, Alabama, to evaluate responses to the range of plausible [CO_2], temperature changes, and precipitation changes projected by climate models out to the end of the 21st century. These sensitivity tests are used to derive crop model emulators that estimate changes in mean yield and the coefficient of variation for seasonal yields across a broad range of climate conditions, reproducing mean yields from sensitivity test simulations with deviations of ca. 2% for rain-fed conditions. We apply these statistical emulators to investigate how peanuts respond to projections from various global climate models, time periods, and emissions scenarios, finding a robust projection of modest (<10%) median yield losses in the middle of the 21st century accelerating to more severe (>20%) losses and larger uncertainty at the end of the century under the more severe representative concentration pathway (RCP8.5). This projection is not substantially altered by the selection of the AgMERRA global gridded climate dataset rather than the local historical observations, differences between the Third and Fifth Coupled Model Intercomparison Project (CMIP3 and CMIP5), or the use of the delta method of climate impacts analysis rather than the C3MP impacts response surface and emulator approach.

Keywords: AgMIP, agriculture, C3MP, climate change, climate impacts, crop model, carbon dioxide, temperature, and water, impacts response surface

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Introduction

Climate change is projected to impact agricultural systems most directly through changes in temperature, precipitation, and carbon dioxide concentration ([CO_2]), with crop responses varying across farms depending on the cultivar, management, soil, and baseline climate. Additional factors (including pests, diseases, weeds, extreme climate events, water resources, soil degradation, agrotechnological development, and economic pressures) will also influence the fate of future agricultural production and deserve scrutiny. There is much to be learned in examining the response of agricultural systems to the core carbon dioxide, temperature, and water (CTW) changes, however (Hatfield *et al.*, 2011).

Crop models provide a biophysical process-based tool to investigate crop responses in light of environmental conditions and farm management, and have been applied to climate impact assessment using a variety of methods (see review by White *et al.*, 2011). The utility of these climate change applications is hindered, however, by the small (1 ha) scale of most process-based crop models, the considerable effort required to achieve satisfactory calibration at a given site, methodological uncertainties, errors in historical climate datasets

Correspondence: Alex Ruane, tel. + 212 678 5640, fax + 212 678 5648, e-mail: alexander.c.ruane@nasa.gov

(Lobell, 2013; Watson & Challinor, 2013), and the lack of agreement among various crop models' responses to CTW changes (Rötter *et al.*, 2011). Most importantly, to date there has not been a coordinated effort to perform climate impacts analyses with a large number of crops, crop models, and detailed crop modeling sites around the world.

While the execution of a single site's crop model is relatively cheap, the coordination of agricultural impacts assessments at larger scales require consistent and timely contributions from a large number of crop modelers, and this effort cannot be duplicated each time a new global climate model (GCM), downscaling technique, or scenario result is created. In addition, evaluation of a subset of GCM simulations is not sufficient to separate important interactions in crop model response. A mechanism is therefore needed to rapidly assess the climate impacts across a wide envelope of climate change space to enable an investigation of uncertainties from any single-GCM or multi-GCM and multi-RCM ensemble (Deser *et al.*, 2012).

The Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013) was created to substantially improve the climate, crop, and economic simulation tools that are used to characterize the agricultural sector, to assess future world food security under changing climate conditions, and to enhance adaptation capacity in both developing and developed countries. AgMIP has led detailed model intercomparisons at highly observed field sites for wheat (Asseng *et al.*, 2013), rice (Li *et al.*, unplublished data), maize (Bassu *et al.*, unpublished data), and sugarcane (Singels *et al.*, 2013), finding largely consistent response patterns across models. It is also clear that crop model selection can be an important factor in an assessment of climate impacts for any given location due to the processes and mechanisms emphasized in the modeling approach. AgMIP is also employing global gridded crop models (GGCMs) to simulate global agricultural production (e.g., Rosenzweig *et al.*, in press, compare 7 GGCMs on a global ½ degree grid) relying on large geodatasets of soil and climate as well as biophysical algorithms to determine likely grid cell inputs for management and cultivars.

The following sections describe a new AgMIP initiative that is coordinating detailed crop model simulations on a global network for climate change impact assessments. To demonstrate the utility of the simulations that will be run at each site and establish a common methodology of evaluation, we present results from a prototype peanut modeling site in Henry County, Alabama, USA. Henry County is a major producer at the center of the Southeastern US peanut belt, and quality soil, meteorology, and management information allow for a robust simulation of yield impacts in light of a changing climate. Results from Henry County are used to discuss the potential benefits of this prototype approach being repeated across a large number of locations, crop species, and crop models to enable more comprehensive climate impacts analysis.

Materials and methods

The Coordinated Climate-Crop Modeling Project (C3MP)

The Coordinated Climate-Crop Modeling Project (C3MP; http://www.agmip.org/c3mp) was created as an AgMIP initiative to provide consistent information about crop yield response to CTW changes across a large, distributed, and global network of established crop modeling sites to facilitate climate impacts assessments. The work builds on earlier efforts at the site scale (Räisänen & Ruokalainen, 2006; Ferrise *et al.*, 2011; Ruane *et al.*, 2013) and at the regional scale (Howden & Crimp, 2005; Crimp *et al.*, 2008; Iizumi *et al.*, 2010) that combine crop model sensitivity tests with crop response emulators (statistical representations of models) across a wide uncertainty space.

All C3MP participants follow a set of common protocols in which contributors register to participate in a crop modeling experiment to execute 99 sensitivity tests, generated using a Latin Hypercube approach, which explore the plausible range of [CO_2], temperature, and precipitation changes projected to occur out at the 2070–2099 time period (Table 1; full protocols are available at http://www.agmip.org/c3mp-downloads). These ranges include the projected extremes from the Fifth Coupled Model Intercomparison Project (CMIP5; Taylor *et al.*, 2009) over the vast majority of agricultural lands and, in fact, are intended to extend slightly beyond this range to ensure that C3MP results remain relevant in the event that more extreme projections become plausible (Fig. 1). In addition to the range of projected temperature increases, sensitivity tests extend to a 1 °C cooling to understand optimal growing conditions which may be cooler than the historical baseline. As the C3MP protocols require the same sensitivity tests for all crop modeling locations, the range of precipitation changes is limited to ±50% to prevent the sensitivity tests from being too sparse in the precipitation change space simply to accommodate arid regions where projections indicate large percentage changes to small historical precipitation totals. It is important to mention that changes in rainfall are restricted to changes in intensity, and changes in the frequency of precipitation events are not taken into account in this study, even though they potentially play an important role in final yields (Baigorria *et al.*, 2007). Whereas the final years of the 21st century have [CO_2] higher than 900 ppm in the highest Representative Concentration Pathway (RCP8.5; Moss *et al.*, 2010), the end-of-century time period (2070–2099) has a central year [CO_2] of 801 ppm. The 330 ppm lower limit of the [CO_2] range helps resolve CO_2 sensitivities around the 1980–2010 historical baseline's central year [CO_2] in 1995 = 360 ppm).

Table 1 Limits of CTW space, relative to baseline climate conditions, explored by sensitivity tests. Corresponding baseline April–August growing season values for Henry County, Alabama, are 24 °C, 581 mm, and 360 ppm, respectively

Climate metric	Lower bound	Upper bound
Temperature change (ΔT)	−1 °C	+8 °C
Precipitation change (ΔP)	−50%	+50%
Carbon Dioxide Concentration ($[CO_2]$)	330 ppm	900 ppm

The sensitivity tests are generated by modifying each day in the 1980–2010 climate series to achieve each test's temperature change (through addition), precipitation change (through a multiplicative factor), and $[CO_2]$ (via an imposed concentration), resulting in 2970 (99 tests × 30 years) yields per simulation set. The mean yield (Y) is then calculated for each sensitivity test and associated with the $[CO_2]$, temperature, and water changes that defined each test. To understand how climate changes may affect yield variability (Osborne & Wheeler, 2013), the coefficient of variation for yield (CV; across the 30 years) is also calculated. This enables the least-squares fitting of a quadratic crop model emulator for Y and CV for any given simulation location as a function of carbon dioxide concentration (CO_2), temperature change (T), and precipitation change (P) to determine coefficients a–k in each of:

$$Y(\mathrm{CO_2},T,P) = a+b(T)+c(T)^2+d(P)+e(P)^2+f(\mathrm{CO_2})+g(\mathrm{CO_2})^2 +h(T*P)+i(T*\mathrm{CO_2})+j(P*\mathrm{CO_2})+k(T*P*\mathrm{CO_2}), \tag{1}$$

and

$$\mathrm{CV}(\mathrm{CO_2},T,P) = a+b(T)+c(T)^2+d(P)+e(P)^2+f(\mathrm{CO_2}) + g(\mathrm{CO_2})^2+h(T*P)+i(T*\mathrm{CO_2})+j(P*\mathrm{CO_2}) + k(T*P*\mathrm{CO_2}). \tag{2}$$

As the emulators for mean yield and yield CV are fit separately, the values of coefficients a–k in Eqn (1) will not be the same as a–k in Eqn (2). In addition, the impacts response surfaces defined by these emulators are a better subject of comparison than the values of specific coefficients (the response to any climatic change is represented in multiple coefficients). The formulation of this crop model emulator will be an important area of ongoing research in C3MP, as it is possible that some locations' mean yield or yield CV responses may be better captured by other forms (e.g., polynomials of a different order or logarithmic functions). Howden & Crimp (2005) used a simpler linear emulator, but then Crimp *et al.* (2008) modified this to include quadratics with different orders of polynomials for $[CO_2]$ (to the fourth order), temperature (to the third order), and precipitation (to the second order). Ruane *et al.* (2013) utilized second-order polynomials to emulate impacts response surfaces for maize in Panama to mimic a yield curve peaking at

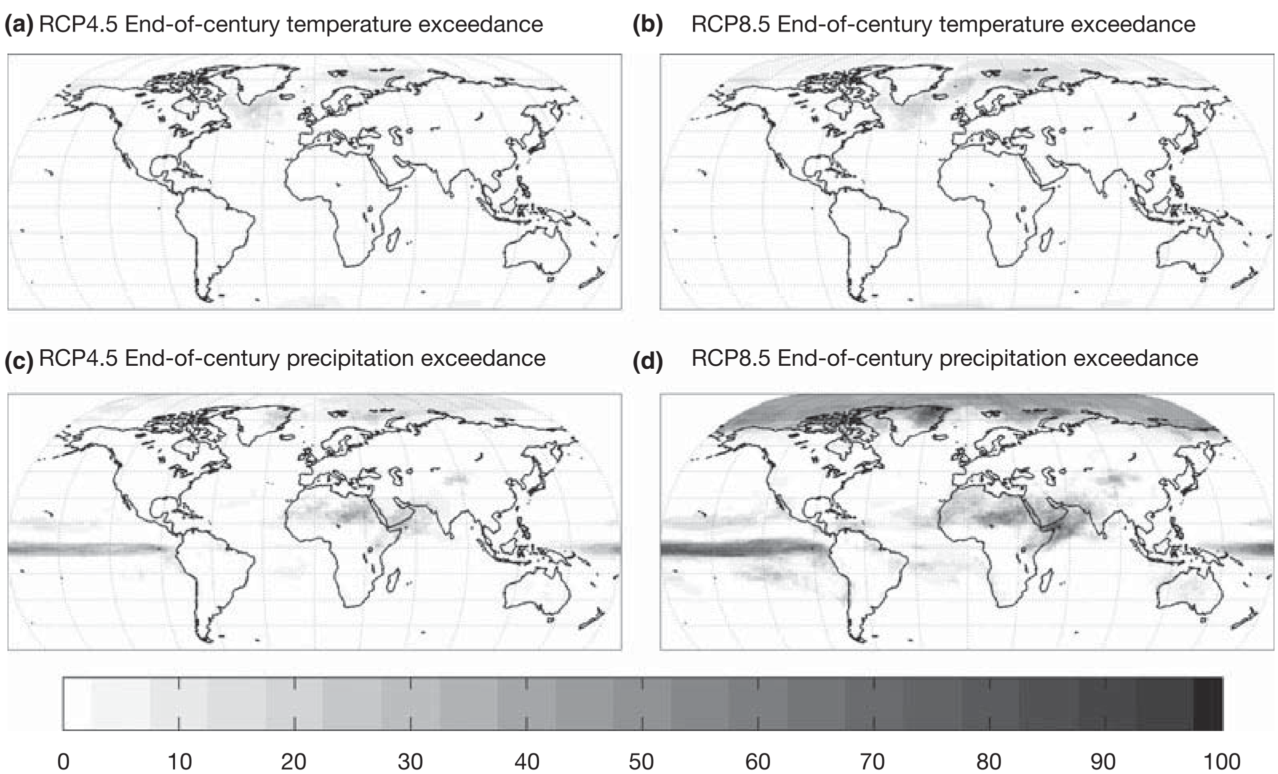

Fig. 1 Percentage of 20 CMIP5 GCMs with daily output where regional annual temperature (a, b) or precipitation (c, d) changes fall outside of the range of C3MP sensitivity tests in the 2070–2099 end-of-century time slice under RCP4.5 (a, c) and RCP8.5 (b, d).

optimal conditions with diminishing returns for increasing [CO_2], but to this point these studies have not included the cross-variable terms in Eqns (1) and (2). These terms allow for non-orthogonal curvature in the crop response space resulting from interactions in the way crop models respond to multiple, simultaneously changing climate variables. These cross-terms are additionally helpful in understanding how correlated climate variables affect yields (Sheehy *et al*., 2006). Ramankutty *et al.* (2013) tested linear, nonlinear, and spline fits for a grassland site in Australia, which could be repeated for any site participating in C3MP. It should also be noted that these climate impact emulators are derived from 30-year climatological crop model results rather than the year-by-year historical climate variability that is often used to develop statistical crop models (e.g., Schlenker & Roberts, 2009; Schlenker & Lobell, 2010). The use of process-based crop models for impacts analysis has the added benefit of including directly resolved interactions between various terms and [CO_2] that may be outside of the range of recent observations in a given region. Lobell & Burke (2010) performed a similar regression using crop model simulations (although based on crop model simulations of interannual variability), finding that quadratic regressions outperformed linear models.

To ensure consistency across sites and encourage the contribution of crop modeling simulations from regions where climate information does not exist or is not available, C3MP provides an estimated daily climate series for the 1980–2010 historical baseline period. Based on the outputs of the NASA Modern Era Retrospective Analysis for Research and Applications (MERRA; Rienecker *et al*., 2011) and MERRA-Land (Reichle *et al*., 2011) outputs, these AgMERRA data (A.C. Ruane, unpublished data) were developed for agricultural impacts applications and are shifted to eliminate apparent monthly biases in comparison to an ensemble of gridded observational data from weather stations and satellites (CRU TS3.10, Harris *et al*., 2013; Willmott & Matsuura, 1995; GPCC, Rudolf & Schneider, 2004; CMORPH, Joyce *et al*., 2004; PERSIANN, Hsu *et al*., 1997; TRMM 3B-42, Huffman *et al*., 2007). AgMERRA also incorporates the NASA-GEWEX Solar Radiation Budget daily radiation data (Zhang *et al*., 2007) which have been shown to be highly useful for agricultural modeling (White *et al*., 2008), and is stored at a resolution of ¼ degree. Where complete and well-vetted station data are available, C3MP participants are encouraged to run both the observational and the AgMERRA climate series through their crop models to gage uncertainties stemming from the selection of baseline climate series.

White *et al.* (2011) summarized the substantial contributions of crop modeling assessments of climate change impacts around the world, finding studies in 69 countries (dominated by North America and Europe) and using 68 crop models. There are many missed opportunities for collaboration, however, because for any given region it is difficult to discover the extent of work that has been completed and to contact crop modelers with experience over the range of agricultural systems. Many sites and models have also been calibrated for operational use, but have never appeared in the peer-reviewed literature. In some cases differences between various modeling studies lead to confusion among the stakeholder and policymaker communities, as multiple assessments in the same region can occasionally produce results that appear contradictory. C3MP is therefore designed to build the network of crop modelers and crop modeling sites around the world to conduct climate vulnerability analyses, enable intercomparison of consistent results, increase communication, and facilitate future collaborations among participants.

A prototype demonstration of the C3MP protocols and enabled analyses is provided below to describe the methods and analyses enabled that are envisioned for all C3MP simulation set locations.

C3MP prototype simulation of peanut yield in Henry County, Alabama

For this prototype simulation set, the core response of peanut yields to climate change was simulated in Henry County, Alabama, which is located near the heart of a productive peanut-growing belt in the Southeastern United States (Fig. 2). An additional site was also configured in nearby Washington County, Florida, for the purposes of regional comparison, but Henry County will be the primary focus of this study.

Peanut simulations were conducted using CROPGRO-Peanut (Boote *et al*., 1998), which is an element of the Decision Support System for Agrotechnology Transfer Cropping System Model (DSSAT-CSM; Jones *et al*., 2003). The sensitivity tests were facilitated by the use of DSSAT's Environmental Modifications function, which modifies historical climate data to achieve each test's temperature, precipitation, and [CO_2]. The key details of the crop model configuration are summarized in Table 2, and describe a rain-fed peanut simulation with planting on April 1st. The simulations use the Georgia Green cultivar, which was calibrated for phenology, biomass, and yield components at field trials

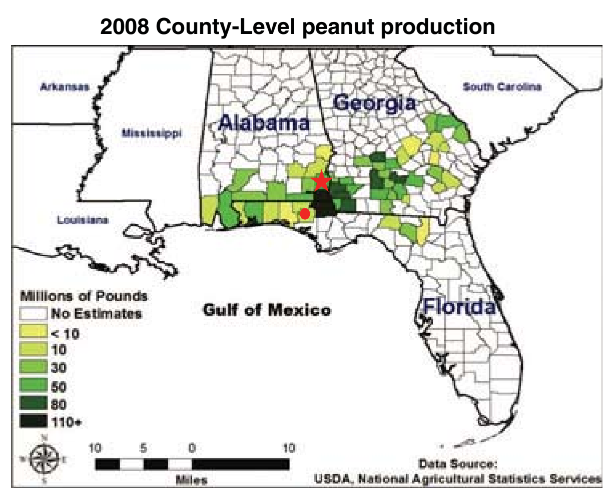

Fig. 2 Location of simulation sites in Southeastern US peanut production region. The symbols indicate Henry County, Alabama (red star), and Washington County, Florida (red circle).

in Tifton, Georgia, and included in DSSAT v4.5 (Hoogenboom et al., 2003). Weather data from 1980 to 2010 were collected from the Florida Climate Center (Office of the State Climatologist, 2012), with radiation estimated from daily temperatures and precipitation. The soil profile was drawn from a reanalyzed soil dataset (Romero et al., 2012), and management followed common local practices. To gage the uncertainty of this configuration and test some of the C3MP analysis methods below, additional simulation sets were also configured. These include a nearly identical simulation set that utilizes an irrigation rule whereby 12 mm applications of irrigation are applied whenever soil water content drops below 70% of plant available water in the top 50 cm of the soil profile. Simulations at Washington County, Florida, were also run that differ only in their use of a local baseline climate series and soil profile. Lastly, the same simulations were run for Henry County using baseline climate series drawn from AgMERRA's corresponding grid box. Note that MERRA likely incorporates a version of the state climatologist data in its underlying data assimilation, so the skill of AgMERRA in this region may be higher than in regions where no local weather stations exist. Peanut simulations in the US Southeast were also conducted by Shin et al. (2010) with a focus on interannual variability.

Results

Historical baseline evaluation

A comparison between simulated peanut yields and the 1980–2010 county-level yields reported by the US Department of Agriculture's National Agricultural Statistics Service (NASS; USDA, 2012) reveals a high level of agreement for the rain-fed simulations driven by the state climatologist observations (Fig. 3; correlation coefficient $r = 0.52$; significant at 0.01 level using t-test). Rain-fed simulations driven by the AgMERRA dataset produced nearly identical correlations ($r = 0.5$; significant at 0.01 level). Irrigated correlations were not significant for either climate series due to the low prevalence of irrigation systems in the region. The performance of rain-fed simulations is particularly strong given that the county-level yields integrate across a variety of management types, soil characteristics, cultivars, and applications across Henry County. Washington County correlations were lower than Henry County, but better for AgMERRA ($r = 0.29$) than for state climatologist observations ($r = 0.19$), likely due to heterogeneous farming practices blurred together in aggregated NASS yield data. The crop model also assumes that pests, diseases, and weeds are perfectly controlled, which is not always the case in the real world.

Table 2 Overview of the rain-fed peanut model simulation set for Henry County, Alabama. A simulation set with irrigation (but otherwise identical) was also conducted, and both simulations were also run for Washington County, Florida, using a local climate series and soil profile. This is the minimum information to be collected for each crop modeling simulation set in C3MP

Simulation set latitude	31.367°N
Simulation set longitude	274.667°E (85.333°W)
Simulation set elevation	112.8 m
Weather data source	State Climatologist
Planting month	April (Julian Day 91)
Typical harvest month	August
Crop model and version	DSSAT v4.5.1.023
Cultivar	Georgia Green
Irrigation applied	None (rain-fed)
Nitrogen applied	0 kg ha^{-1}
Soil profile latitude	31.2°N
Soil profile longitude	274.92°E (85.07°W)
Soil profile source	Reanalyzed soils (Romero et al., 2012)

CTW response surfaces

The emulators fit by Eqns (1) and (2) allow for the estimation of crop model response to any point in the CTW change space for Henry County peanuts. To test the skill of this emulator against the direct simulation of a given scenario, each of the sensitivity tests was estimated using the emulator and compared to the crop model's simulation of that test, resulting in root mean square deviations (RMSD, as a percentage of mean 1980–2010 yield) of 1.90% and 1.96% for rain-fed conditions with the observed climate and AgMERRA, respectively, and Pearson's correlations (r^2) greater than 0.99. For irrigated conditions mean yield RMSD were slightly smaller (1.25% and 2.3% for the two climate series). Omitting 20 of these sensitivity tests randomly did not substantially change the emulator, with RMSD changing by less than 0.1% of the mean yields and r^2 remaining above 0.99. Yield CV had higher emulator RMSD in the rain-fed conditions (2.30% and 3.37%; $r^2 > 0.99$), and much higher RMSD for irrigated conditions (9.36% and 6.96%; $r^2 > 0.98$), although the latter is a result of the much smaller CV for irrigated conditions that face little or no interannual water stresses. Overall, the emulators appear to be robustly capturing the core response of the crop model regardless of the baseline climate series utilized. These emulators may technically be extrapolated outside of the C3MP climate change limits defined in Table 2; however, this must be done with caution as the statistical properties of the moderate-to-large climate changes may not hold in the case of more extreme climate changes.

The three-dimensional CTW space is most easily examined by looking at cross sections where one of the

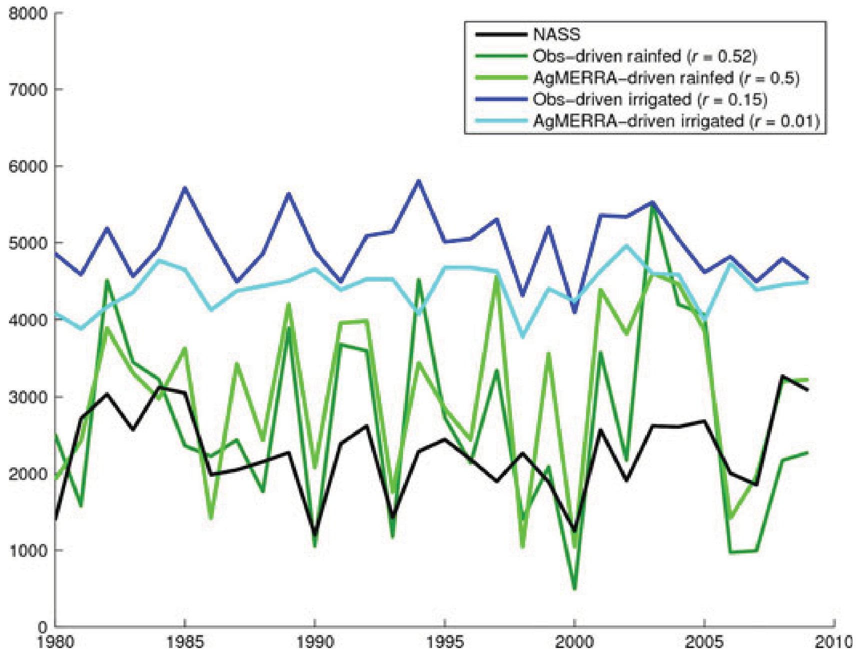

Fig. 3 Simulated rain-fed and irrigated yields in comparison to the National Agricultural Statistics Service (NASS) reported peanut yields for Henry County, Alabama.

climate change metrics is kept at the baseline level (Fig. 4). The general response of rain-fed Henry County mean yields is as might be expected, but the general decrease in yields under warmer and drier conditions with lower [CO_2], as well as the increase in yields in cooler, wetter, and higher [CO_2] environments may now be quantified. Yield CV responds most strongly to precipitation (wetter conditions leading to lower CV and more consistent interannual yields), although warmer conditions have the potential to offset CV decreases from wetter conditions, probably through a combination of increased evapotranspiration and a closer proximity to damaging high-temperature thresholds.

These emulators enhance our understanding of crop model responses in their ability to identify nonlinearities in crop response, explore interactions in CTW response, and quickly assess climate change scenarios. For example, if [CO_2] is held at the baseline levels (Fig. 4a), the sensitivity of mean yield to rising temperatures is higher under wet conditions than under drier conditions, indicating that peanut is more responsive to heat stress when there is no competing water stress. Likewise, if temperatures are held at the baseline levels (Fig. 4c and d), an increase in [CO_2] to 700 ppm can offset mean yield losses resulting from a 30% decrease in growing season precipitation, although the yield CV will increase by about 25%. Finally, if precipitation is held constant (Fig. 4e), peanut responds to rising [CO_2] in a nearly linear fashion if temperatures do not change but shows diminishing returns and very little response beyond about 600 ppm when temperatures increase by more than 5 °C.

To further explore the robustness of these emulators and the potential for broader C3MP analysis, Fig. 5 presents differences between the impacts response cross sections calculated using different climate series (left column), different locations (middle column), and different irrigation regimes (right column). There is very little difference between an emulator based on the sensitivity tests applied to the observational climate dataset and that created from sensitivity tests applied to the AgMERRA dataset. A comparison between Figs 4c and 5c suggests that the use of the AgMERRA climate dataset leads to slightly less optimistic simulations of the yield benefits when both [CO_2] and precipitation rise dramatically, but the overall pattern of response is very similar. The AgMERRA dataset is therefore a suitable alternative for the C3MP exercise for peanut simulations in Henry County, which encourages its further application in regions where observational data are not available. Differences between the observed weather data and the AgMERRA estimates will also elucidate agricultural regions where gridded climate datasets may be missing key agroclimatic processes.

Although Henry and Washington Counties are only ca. 100 km apart and have small differences in mean climate, lower root zone soil saturation levels in Henry County lead to unique CTW responses. This is apparent

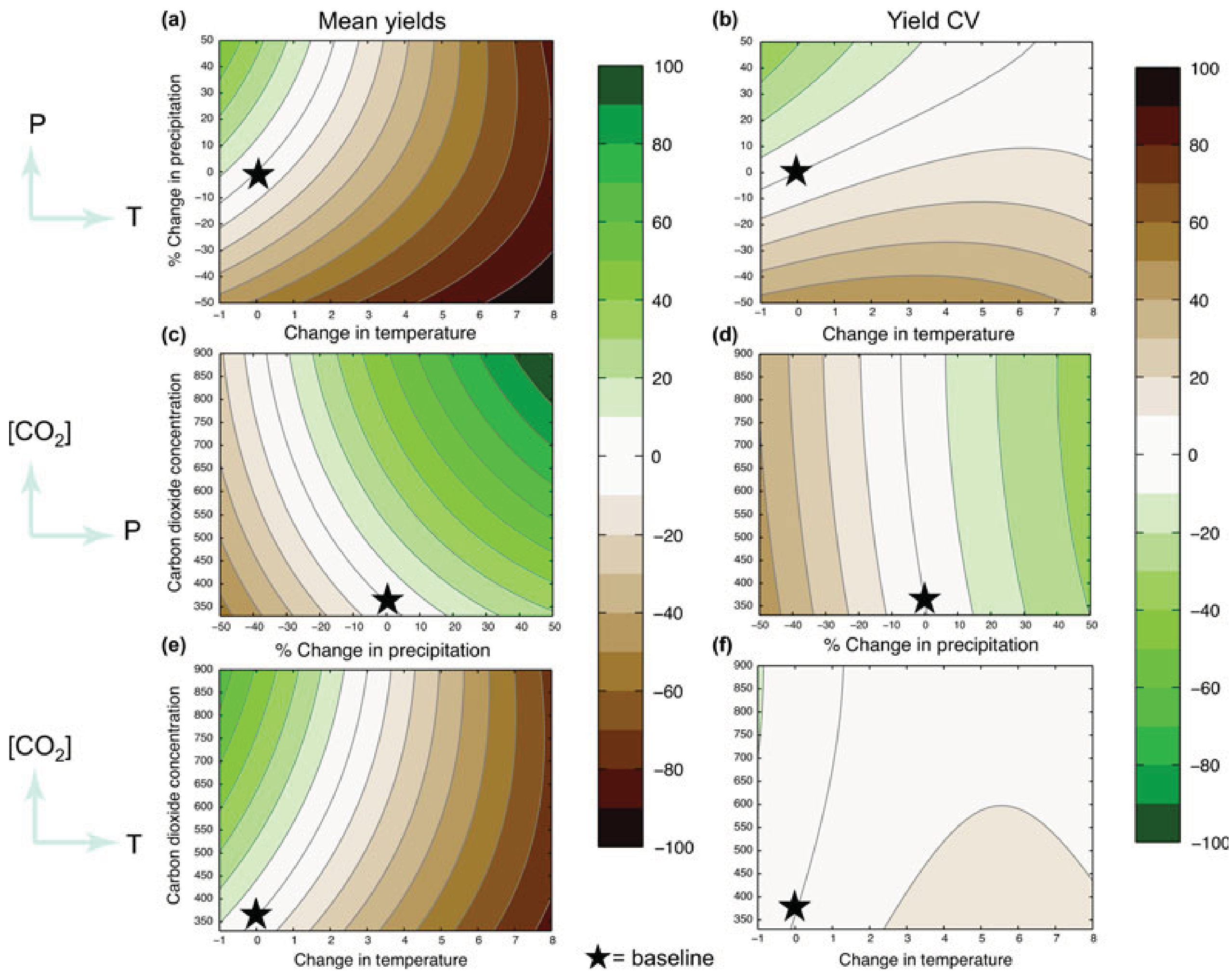

Fig. 4 Cross sections of crop model emulators based upon sensitivity test results for percent changes (relative to baseline conditions) of mean peanut yield (a, c, e; left color bar) and changes in the coefficient of variation for yield (b, d, f; right color bar) in Henry County, Alabama, for (a–b) temperature and precipitation response at baseline [CO_2]; (c–d) precipitation and [CO_2] at baseline temperature; and (e–f) temperature and [CO_2] at baseline precipitation. The black stars in each panel represent baseline conditions (no change in temperature or precipitation and 360ppm [CO_2]).

in the baseline period CVs, which are nearly twice as high in Henry County (0.47) as they are in Washington County (0.26) due to a higher sensitivity to drought conditions (correlations between rain-fed yield and growing season precipitation are 0.79 and 0.62, respectively; both significant at P = 0.001 level). The overall pattern of impacts response in Henry and Washington Counties is consistent (Fig. 5, center column), although Washington County is less sensitive to changes in precipitation. This highlights the role of water stress as the major difference between these locations' CTW responses, and their differences look very similar to (although weaker than) the differences between rain-fed and irrigated conditions at Henry County (Fig. 5, right column; which represent a nearly complete elimination of water stress). A comparison between the rain-fed and irrigated conditions also helps quantify the benefits of irrigation as an adaptation for future climate changes. Both respond in a similar fashion when temperature increases are above 4 °C and precipitation is at least as much as in the present climate. Rain-fed conditions at Henry County are also more responsive to the benefits of elevated [CO_2] than Washington County and the irrigated Henry County simulations, illustrating the effects of improved water retention in high-CO_2 environments (Kimball, 2010).

Instantaneous sensitivities

The framework allows for the calculation of the instantaneous sensitivity to changes in carbon, temperature, and water by calculating the slope of the emulated

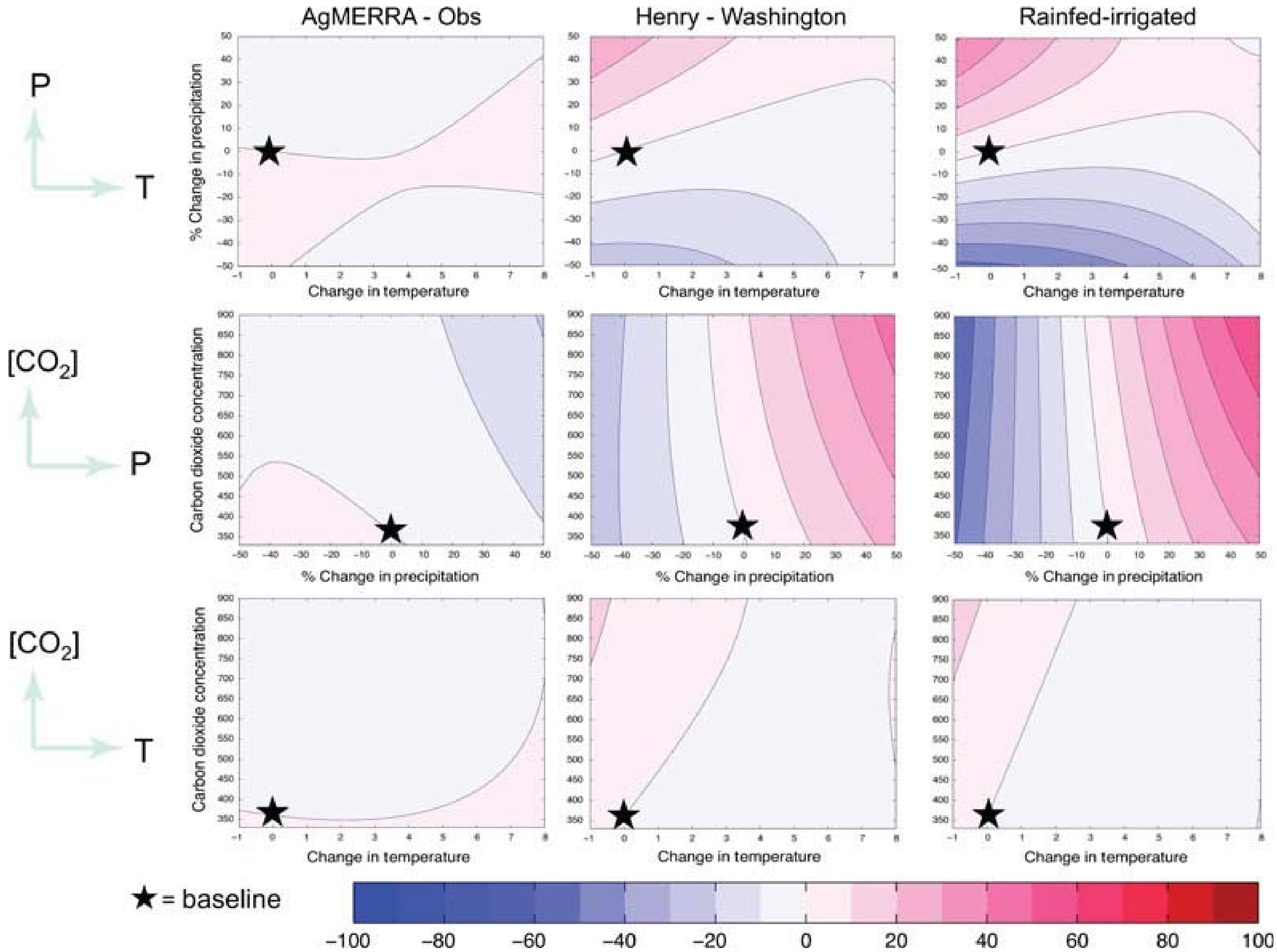

Fig. 5 Differences (as percent of baseline) between emulated responses for mean peanut yield (following Fig. 4a, c, e) between the AgMERRA and observed climate series for rain-fed conditions at Henry County (left); Henry and Washington Counties using the observed climate series under rain-fed conditions (center); and rain-fed and irrigated conditions at Henry County using the observed climate series.

yield response surface at any given point. If we assume that the response of peanut yield to temperature and precipitation changes takes the shape of a curved surface that peaks at optimum conditions, the optimal growing season climate is found where the slope of this temperature–water surface is zero (crops are assumed to respond favorably to increased [CO_2] in all climates). In general, yields are expected to fall off at an accelerating pace as the climate moves away from these optimal conditions, but the historical baseline climate is not necessarily optimal. It is important to note that the sensitivities calculated from the C3MP emulators are based on 30-year climate shifts, which likely differ from yield sensitivities to interannual climate shifts (Ruane *et al.*, 2013).

The instantaneous sensitivities of peanut simulations in Henry County to changes away from its historical baseline climate (marked with a star in Figs 4 and 5) indicate that optimal conditions are somewhat cooler and wetter than the 1980–2009 climate. Yields decrease by 11.7% per 1 °C rise in mean growing season temperature, and increase by 8.5% per 10% increase in mean growing season rainfall. Under irrigated conditions mean yield decreases 8.6% per 1 °C rise and there is no response to increasing rainfall (indicating that irrigation acts as optimal water conditions). Rain-fed and irrigated peanuts respond to a 100 ppm increase in [CO_2] with similar 12.8% and 11.2% increases in yield, respectively.

Probabilistic Analysis of CMIP5 projections

The C3MP impacts response surfaces also extend the utility of the 99 sensitivity tests by enabling specific scenarios to be rapidly explored. As any scenario can be summarized by its growing season [CO_2], temperature change, and precipitation change from the historical baseline period, these CTW changes can be plugged into the emulators to estimate agricultural impacts.

As an illustration, Fig. 6a shows the projected changes in temperature and precipitation for Henry County, Alabama, across various time slices in an ensemble of 20 GCMs that contributed to CMIP5. These 20 GCMs are the subset that had posted (as of October, 2012) daily output through at least 2099 for RCPs reflecting higher (RCP8.5) and lower (RCP4.5) [CO_2]. The projections agree on progressive warming over the course of the 21st century; however, the rate of that warming is highly dependent on the RCP and there is little agreement on the direction of precipitation changes. Incorporating [CO_2] determined for any given time slice from the RCP, each GCM time-slice projection was emulated to produce probabilistic estimates of particular yield and yield CV thresholds according to the CMIP5 ensemble (Table 3).

Examining an extreme yield threshold defined by mean 30-year yields that are only 80% of the mean yields in the historical baseline, the CMIP5 GCMs suggest that farmers in Henry County do not face a 20% mean yield decrease until the end-of-century (2070–2099) period under RCP4.5 (when only 17 of the 20 models have emulated mean yields above this threshold). Under RCP8.5, however, this level of threat is reached in the mid-century (2040–2069) and a minority of the GCMs project yields above this threshold during the end-of-century time slice. On the other end of the spectrum, farmers hoping for even modest mean yield increases (>105% of the baseline) find only a 25% probability in the near-term (2010–2039) under RCP4.5 and then a 10% change beyond that period. Results are similar for irrigated peanut, although the probability of yield increases is slightly lower (5%).

Yield CV is also projected to increase with very high probability. For rain-fed conditions only 40% of models project CVs less than the baseline period in the near term, with probabilities declining in future periods in both RCPs. CVs are projected to increase to more than 120% of their baseline value by the midcentury period with high probability under irrigated conditions (where CV is already quite small), with all models projecting higher than 40% increases in CV at the RCP8.5 end of century.

Comparison of CMIP5 and CMIP3 projections

To compare between the current state of the art and the projections used for a large number of previous climate change impact studies, Fig. 6b shows a comparison in projected growing season mean temperature and precipitation changes among the same 20 CMIP5 GCMs under RCP8.5 and 16 GCMs from the higher emissions scenario (A2; SRES, 2000) of the previous-generation CMIP3 (Meehl *et al.*, 2007). CMIP3 and CMIP5 results potentially disagree due to updates in GCM resolutions, parameterizations, and processes, as well as differences between the RCP8.5 and A2 scenarios' evolution of greenhouse gas concentrations. RCP8.5 reaches higher [CO_2] by the end-of-century period than does A2 (801 ppm and 734 ppm in 2085, respectively), although values are much closer in the near-term (432 ppm and 434 ppm in 2025) and mid-century (571 ppm and 556 ppm in 2055). Even with a larger number of models, the CMIP5 projections are in stronger agreement as to Henry County temperature and precipitation changes than are the CMIP3 projections, although the most extreme temperature changes are projected under CMIP5's higher [CO_2] RCP8.5 scenario.

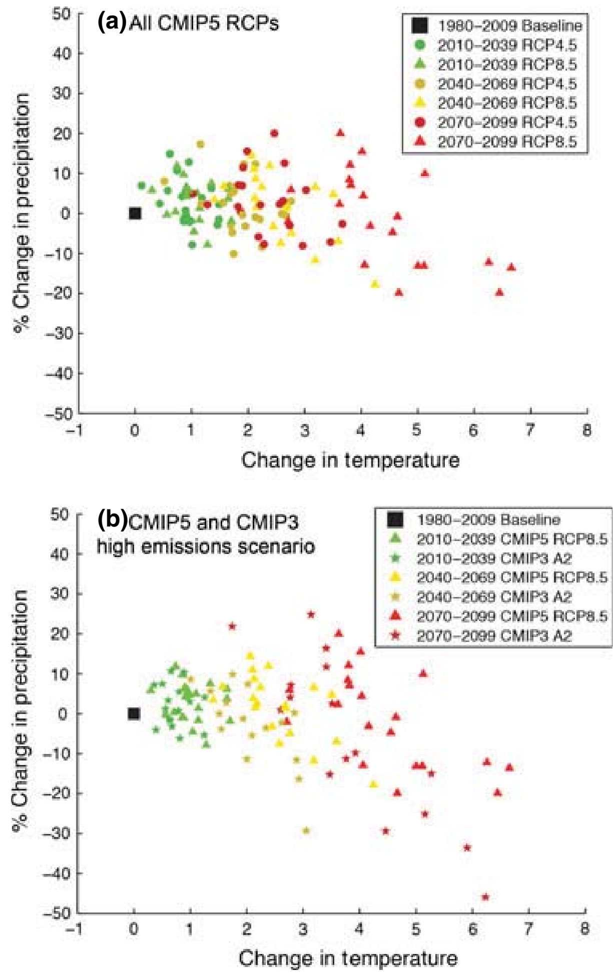

Fig. 6 Projected changes in growing season (April–August) mean temperature and precipitation for Henry County, Alabama, for three 30-year time slices relative to the 1980–2009 baseline from (a) 20 CMIP5 GCMs run with a higher (RCP8.5) and lower (RCP4.5) concentrations pathway, and (b) the same CMIP5 points from the higher concentrations pathway in addition to 16 GCMs from CMIP3's higher (A2) emissions scenario experiments.

Table 3 Probabilistic threshold analysis of CMIP5 results under rain-fed (a, c) and irrigated (b, d) conditions for peanut. Results indicate the percentage of GCMs where emulators project that a given threshold will be surpassed for mean yield (a, b) and yield CV (c, d), and are color coded with white = 100%, light gray = 70–99%, medium gray = 30–69%, and dark gray = 0–29%

	RCP4.5			RCP8.5		
	Near-term	Mid-century	End-of-century	Near-term	Mid-century	End-of-century
(a) Rain fed						
Mean Yield > 80% of Baseline	100	100	85	100	85	45
Mean Yield > 90% of Baseline	85	60	55	90	50	30
Mean Yield > 100% of Baseline	40	25	35	45	30	10
Mean Yield > 105% of Baseline	25	10	10	15	15	5
(b)Irrigated						
Mean Yield > 80% of Baseline	100	100	95	100	95	55
Mean Yield > 90% of Baseline	100	85	70	100	75	20
Mean Yield > 100% of Baseline	25	15	10	20	10	10
Mean Yield > 105% of Baseline	5	5	5	5	5	0
(c) Rain fed						
CV < 95% of Baseline	20	10	5	5	0	0
CV < 100% of Baseline	40	20	25	40	25	15
CV < 120% of Baseline	100	100	100	100	95	95
CV < 140% of Baseline	100	100	100	100	100	100
(d) Irrigated						
CV < 95% of Baseline	0	0	0	0	0	0
CV < 100% of Baseline	0	0	0	0	0	0
CV < 120% of Baseline	75	15	5	75	0	0
CV < 140% of Baseline	100	75	45	100	45	0

In general, GCMs in a given time period projecting larger precipitation decreases also project greater warming, indicating a shift in the ratio of latent and sensible energy fluxes as surface moisture changes.

The emulated yield change distributions presented in Figure 7 show that the general message of climate impact projections for rain-fed and irrigated peanut production in Henry County has not changed dramatically from CMIP3 to CMIP5, with both ensembles suggesting yield declines by midcentury and accelerating losses into the end-of-century period. CMIP5 RCP8.5 projections suggest slightly larger yield losses than do the CMIP3 A2 simulations; however, the CMIP3 ensemble shows larger uncertainties in the end-of-century period. The latest CMIP5 projections are therefore more consistent and more pessimistic than would have been assessed in previous-generation CMIP3 impact studies, resulting in CMIP3's most severe and most optimistic end-of-century projections being eliminated.

Comparison of simulated and emulated climate change impact projections

As a final check on the efficacy of the C3MP sensitivity tests and emulator approach for Henry County peanuts, Figure 8 presents a comparison between the distribution of CMIP5 yield change projections using the C3MP emulators and the distribution resulting from an impacts assessment using the more traditional "delta method" (Wilby *et al.*, 2004; White *et al.*, 2011). In the latter approach, changes in mean monthly temperatures and precipitation (calculated by comparing the climatologies of a future time slice with the historical baseline period in a given GCM) are imposed on the observed historical period climate series and then used to drive crop model simulations.

The emulated yield change distributions and directly simulated yield change distributions indicate the same general response of Henry County peanuts to CMIP5 climate changes, with yields declining modestly to the mid-century and then accelerating losses by the end-of-century period. Median yield change projections (red lines in Fig. 8a–d) are similar; however, the emulated yields underestimate the spread in uncertainty suggested by the delta method simulations. Direct comparison between the emulated and simulated yield change projections across all GCMs and time periods (Fig. 8e–h) reveals that the emulators tend to be somewhat conservative, underestimating the most extreme yield decreases and increases (a similar underestimation was found by Lobell & Burke, 2010). In this case the discrepancy is likely a combination of the least-squares fitting of the emulator as well as differences between using mean growing season temperature and precipitation

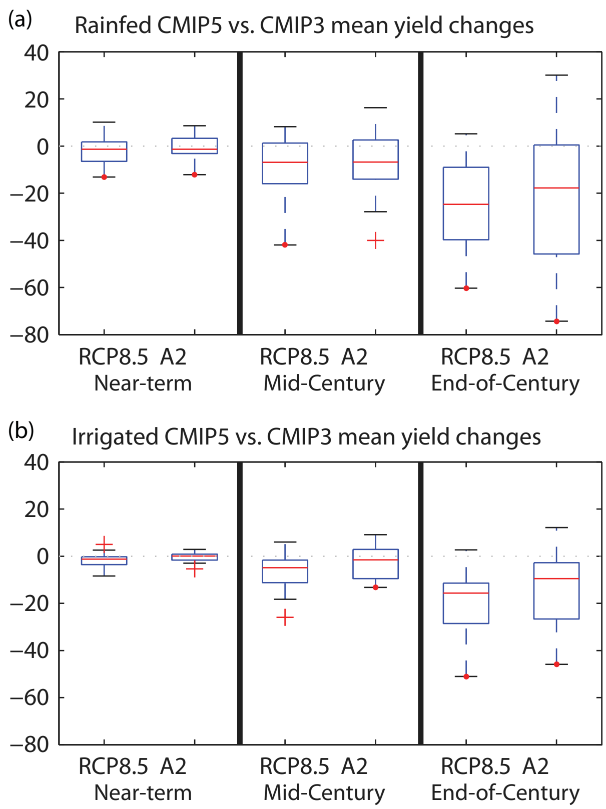

Fig. 7 Comparison of mean yield changes from three future time slices (near term, midcentury, and end of century relative to baseline mean) between the higher [CO_2] scenarios of 20 CMIP5 GCMs (*RCP8.5*) and 16 CMIP3 GCMs (A2) for (a) rainfed and (b) irrigated conditions.

changes for the emulator and monthly changes for the delta method simulations. Several GCMs have substantial variation in the way that climate changes within a growing season; however, these changes do not have as dramatic an impact when averaged over a longer growing season. As C3MP is designed to require only a small set of sensitivity tests from its global participants, investigation of these subseasonal impacts is left to follow-on studies.

Discussion

The prototype study at Henry County, Alabama, reveals the potential insight and analyses enabled by the execution of C3MP sensitivity tests. With only a relatively small set of simulations, crop modelers around the world are able to provide the crucial carbon dioxide, temperature, and water responses that govern the main agricultural response to climate change. Analysis of GCM projections and the CTW impacts response surfaces at Henry County reveal modest yield losses accelerating beyond the middle of the 21st century, with temperature and water stresses overwhelming the benefits of enhanced [CO_2]. Generalized crop model emulators provide a robust fit to the sensitivity tests, and results are consistent between this approach and the more involved delta method approach. These emulators allow future scenarios to be rapidly assessed for Henry and Washington County peanuts as was done here for various RCPs, GCMs, and time periods. Yield (or CV) change threshold analysis also facilitates risk management either by probabilistic projection (Table 3) or in terms of identifying the types of climate changes that cross important change contours in Fig. 4. Simulations based on the AgMERRA climate data also satisfactorily reproduce those based on the state climatologist observations, motivating expanded applications of these data where local observations are not available.

This analysis at the Henry County site is informative, but the coordination of a global network of C3MP sites enables larger analyses including the identification of vulnerable subregions and cropping systems in a given region, the relative sensitivities to immediate changes in temperature or precipitation, the forms of emulators that are robust in various farming systems, and the general agreement between crop models or sites with slightly different cultivars and/or farm management. C3MP results will also increase our ability to gage uncertainties across regions, scenarios, and crop models, as well as providing points of comparison for global gridded crop model improvement and examinations of scale dependency in impacts assessment. When C3MP crop model emulators are combined with climate model emulators under development in the climate modeling community that produce regional temperature and precipitation changes based on carbon dioxide concentrations (e.g., Castruccio *et al.*, in review), the combination will allow for rapid statistical assessment of regional climate impacts based on greenhouse gas emissions simulated by integrated assessment models.

It is also important to recognize limitations in the C3MP approach. A focus on growing season temperature and precipitation changes neglects the likelihood of subseasonal changes in the frequency, distribution, and extremes of these variables, which could substantially affect regional yield changes. C3MP also neglects to differentiate between changes in minimum temperature and maximum temperature despite a strong physical basis to expect the former to slightly outpace the latter. C3MP assumes that current management practices will persist under future climate conditions, leading to a more pessimistic projection that is better used to recognize the risk of ignoring climate impacts. In light of these limitations, C3MP will be of most use for rapid assessment of new scenarios and to identify

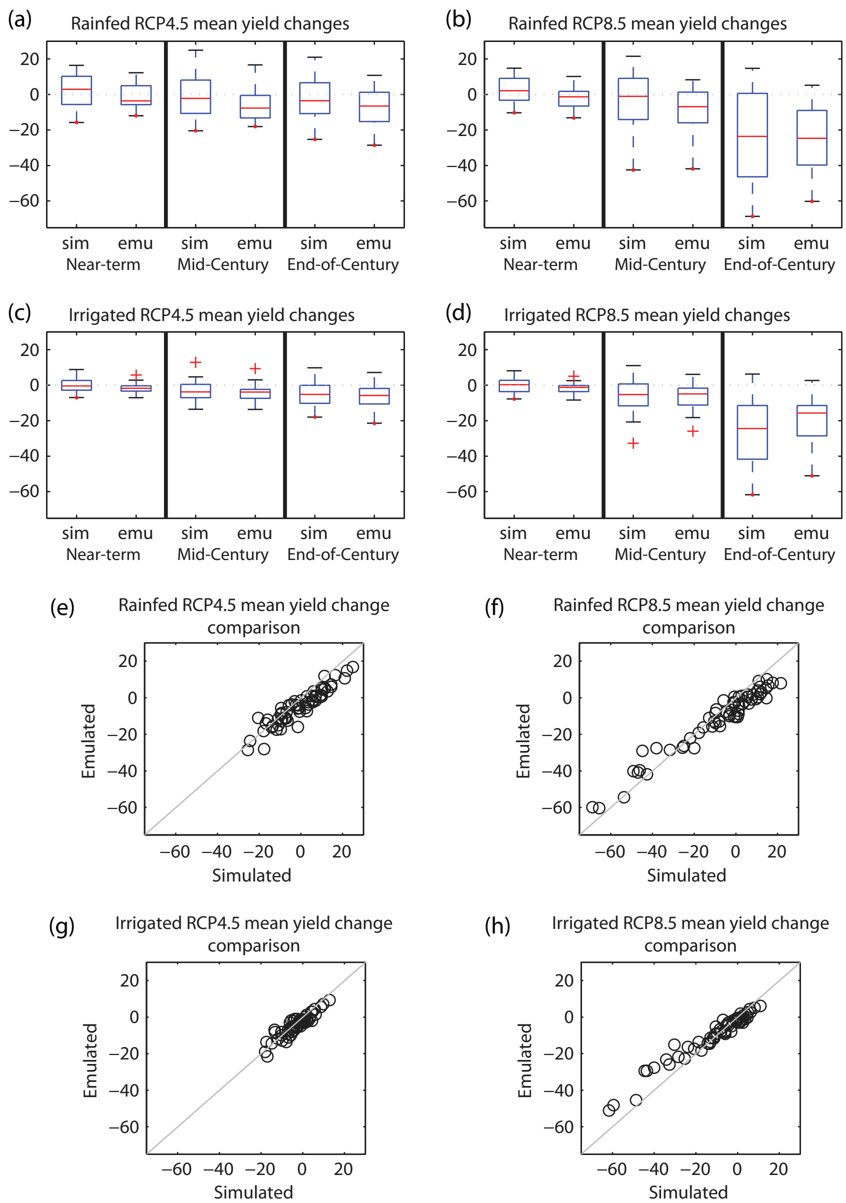

Fig. 8 Comparison of mean peanut yield changes from three future time slices (near term, midcentury, and end of century relative to baseline mean from left to right in each panel) between directly simulated delta scenarios (*sim*) and the corresponding emulator-based estimates (*emu*) across 20 CMIP5 GCMs for the RCP4.5 (a, c) and RCP8.5 (b, d) concentrations pathways and for rain-fed (a–b) and irrigated (c–d) conditions. Panels (e–h) show the direct comparison of all GCMs and time slices for (e, g) RCP4.5 and (f, h) RCP8.5 under (e–f) rain-fed and (g–h) irrigated conditions, along with a 1 : 1 line for comparison.

major vulnerabilities and responses that merit more comprehensive investigation by regional experts.

C3MP increases (and encourages) collaboration among the global network of participants and motivates further studies that can be designed to answer specific questions of crop response to particular stresses or differences between various crop model performances in a given farming system. High-quality experiments, free-air carbon enrichment (FACE; Kimball, 2010) facilities, and other field trials are still required to most accurately quantify CTW sensitivities and improve these model simulations and the associated emulators. AgMIP research projects are underway to improve regional impacts assessment and increase the number of calibrated crop modeling sites around the world, as well as to connect the lessons learned from C3MP and other initiatives to future assessments of food security at local, regional, and global scales.

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