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The combined and separate impacts of climate extremes on the current and future US rainfed maize and soybean production under elevated CO_2

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Abstract

Heat and drought are two emerging climatic threats to the US maize and soybean production, yet their impacts on yields are collectively determined by the magnitude of climate change and rising atmospheric CO_2 concentrations. This study quantifies the combined and separate impacts of high temperature, heat and drought stresses on the current and future US rainfed maize and soybean production and for the first time characterizes spatial shifts in the relative importance of individual stress. Crop yields are simulated using the Agricultural Production Systems Simulator (APSIM), driven by high-resolution (12 km) dynamically downscaled climate projections for 1995–2004 and 2085–2094. Results show that maize and soybean yield losses are prominent in the US Midwest by the late 21st century under both Representative Concentration Pathway (RCP) 4.5 and RCP8.5 scenarios, and the magnitude of loss highly depends on the current vulnerability and changes in climate extremes. Elevated atmospheric CO_2 partially but not completely offsets the yield gaps caused by climate extremes, and the effect is greater in soybean than in maize. Our simulations suggest that drought will continue to be the largest threat to US rainfed maize production under RCP4.5 and soybean production under both RCP scenarios, whereas high temperature and heat stress take over the dominant stress of drought on maize under RCP8.5. We also reveal that shifts in the geographic distributions of dominant stresses are characterized by the increase in concurrent stresses, especially for the US Midwest. These findings imply the importance of considering heat and drought stresses simultaneously for future agronomic adaptation and mitigation strategies, particularly for breeding programs and crop management. The modeling framework of partitioning the total effects of climate change into individual stress impacts can be applied to the study of other crops and agriculture systems.

Keywords: Agricultural Production Systems Simulator, climate change, drought, elevated CO_2, heat, maize, soybean

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Introduction

The US agriculture system is the world's largest producer of maize and soybean and typically supplies more than one-third of their global trading (USDA, 2015). Nearly 90% of the US maize and soybean productions are rainfed (NASS, 2013) and are thus susceptible to adverse climatic conditions. As climate changes, the risks of climate extremes such as heat waves and droughts have been increasing (Diffenbaugh & Ashfaq, 2010; Mishra *et al.*, 2010; Gao *et al.*, 2014) and have already threatened the US agricultural system (Melillo *et al.*, 2014). For example, the 2012 US drought and the co-occurring heat wave reduced maize and soybean production in the US Midwest by 13% and 3% compared to the previous year, respectively (NASS, 2013). Therefore, understanding the current and future impacts of climate extremes on the US maize and soybean production is greatly needed.

The negative impact of high temperature on crop production, commonly referred to as 'heat stress', has been identified for maize and soybean with sufficient evidence (Prasad *et al.*, 2008; Schlenker & Roberts, 2009; Djanaguiraman *et al.*, 2011; Lobell *et al.*, 2013; Eyshi Rezaei *et al.*, 2015). A number of mechanisms could potentially explain the observed relationship, including but not limited to: sensitivity of anthesis–silking period to high temperature (Bolanos & Edmeades, 1996), declines in net photosynthesis (Prasad *et al.*, 2008; Eyshi Rezaei *et al.*, 2015), hastening leaf senescence (Parent

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& Tardieu, 2012) and changes in atmospheric water demand and soil water supply (Lobell *et al.*, 2013, 2014). Drought, the insufficient water supply to meet plant growth demand, can adversely affect crop growth and yield through limiting leaf expansion, photosynthesis, carbon allocation, yield formation, growth of rooting system and through accelerating senescence (Prasad *et al.*, 2008). Maize production in the US Midwest has become more sensitive to drought than soybean for the past two decades, possibly due to a higher increasing trend of sowing density in maize (Lobell *et al.*, 2014) and growth behavior (*viz.* determinate vs. indeterminate species; Connor *et al.*, 2011). Substantial increase in concurrent heat and drought has been observed in the contiguous USA since the 1950s (Mazdiyasni & AghaKouchak, 2015), causing greater agricultural risks compared with years when these events occur singly or one follows another. The critical role of extreme heat for the US maize and soybean appears to be a result of its nonlinear effects on vapor pressure deficit (VPD), as high VPD not only exacerbates short-term water demand but also lowers future soil water supply (Lobell *et al.*, 2013, 2014; Urban *et al.*, 2015). Although heat and drought stress seems to be intertwined with each other, distinguishing the role of heat and drought in yield losses is important for developing comprehensive strategies for breeding and field management when farmers have to cope with both stresses (Lobell *et al.*, 2015).

Elevated atmospheric carbon dioxide (CO_2) further complicates the quantification of heat and drought stress on maize and soybean growth. By reducing stomatal openness, elevated atmospheric CO_2 ([CO_2] hereafter) leads to decreased crop transpiration and increased soil moisture storage (Long *et al.*, 2006; Bernacchi *et al.*, 2007; Leakey *et al.*, 2009; Bunce, 2014; Madhu & Hatfield, 2014), thus ameliorating the potential drought stress and benefiting yield (Leakey *et al.*, 2006; Hussain *et al.*, 2013; Lobell *et al.*, 2015; Urban *et al.*, 2015). Nonetheless, the reduction in canopy latent heat as a side effect of less water fluxes will elevate the leaf temperature and will affect rates of photosynthesis and respiration, thus net productivity (Bernacchi *et al.*, 2005; Long *et al.*, 2006; Twine *et al.*, 2013). Crops grown under elevated [CO_2] may express higher thermotolerance of photosynthesis, but this is more likely for C3 (e.g., soybean) rather than C4 (e.g., maize) species (Taub *et al.*, 2000; Wang *et al.*, 2008). On the other hand, CO_2 directly stimulates C3 photosynthesis and compensates a portion of the climate-induced yield losses (Long *et al.*, 2006; Bishop *et al.*, 2015). This so-called CO_2 fertilization effect is anticipated because major C3 crops are CO_2 limiting under the current atmosphere (Chapin *et al.*, 2011), and elevated [CO_2] can increase their radiation utilization and net photosynthesis by raising the intercellular CO_2 substrate and inhibiting the competing photorespiration (Long *et al.*, 2006; Dermody *et al.*, 2008; Leakey *et al.*, 2009). For C4 crops that are CO_2 saturated under current atmospheric conditions, the effect of rising [CO_2] on yield is more controversial, in that earlier enclosure studies reported significant fertilization effect but more recent free-air concentration enrichment (FACE) experiments found only small responses (Long *et al.*, 2006; Ainsworth *et al.*, 2008). The stimulation of maize yield is likely to be prominent only under drought conditions and would rather be an indirect effect of water savings due to stomatal closure than a stimulation of photosynthesis (Leakey *et al.*, 2006; Twine *et al.*, 2013).

Process-based crop models are powerful tools for investigating the complex interactions among heat, drought and elevated [CO_2], although the quantitative relationships between yield and these factors remain uncertain (Lobell *et al.*, 2013; Bassu *et al.*, 2014; Rosenzweig *et al.*, 2014). Twine *et al.* (2013) simulated the surface energy budget of maize and soybean in the US Midwest with the Agro-IBIS model and found elevated [CO_2] from 375 to 550 ppm suppressed canopy latent heat flux but increased sensible heat flux for both crops, which ameliorated drought stress and stimulated soybean yield of ca. 10% averaged over 30 years and maize yield of ca. 10% during dry years. A recent study that applied the PEGASUS model with 72 climate change scenarios showed that elevated [CO_2] substantially counteracted the extreme heat stress during the crop reproductive phase by the 2080s (Deryng *et al.*, 2014). By using the Agricultural Production Systems Simulator (APSIM) at representative field cropping sites in the northeastern Australia, Lobell *et al.* (2015) concluded that elevated [CO_2] increased sorghum (a C4 species) transpiration efficiency (TE) and partially offset drought effects that were exacerbated by the concurrent rising VPD during the 21st century and that warming relieved spring drought for winter wheat (a C3 species) by hastening phenology, while elevated [CO_2] further benefited the yield by increasing both radiation use efficiency (RUE) and TE. However, existing modeling studies have not yet given an explicit method for separating the yield responses to individual climate stress given the confounding factor of elevated [CO_2]. More efforts are thus needed to advance the understanding and the predictability of these complex interactions at different geographic domains, in order to inform crop breeding and management.

In this study, we use the APSIM modeling platform, driven by high-resolution (12 km) dynamically downscaled climate projections, to investigate the impacts of future climate extremes on the US maize and soybean production. Specifically, we answer four questions: (i)

How do future climate extremes affect the yield of US corn and soybean? (ii) How do individual climate extremes shift in their relative importance and geographic distributions? (iii) How much can CO_2 fertilization compensate the yield loss caused by climate extremes? and (iv) How to reduce prediction uncertainty in crop yield responses.

Materials and methods

APSIM description

Agricultural Production Systems Simulator is an agricultural system modeling platform that can simulate the growth of a number of crops under various climatic, edaphic and management conditions and hence is used worldwide to address a range of research questions related to cropping systems (Keating *et al.*, 2003; Holzworth *et al.*, 2014). Maize and soybean modules in APSIM are incorporated with a number of processes at a daily time step such as phenology, morphology, crop physiology, biomass production and partitioning and yield formation in response to management, weather conditions and soil water and nitrogen stresses. In recent years, APSIM has been successfully applied in the USA to investigate the impact of changing maize canopy and root structure on yield (Hammer *et al.*, 2009), the sensitivity of heat and drought on maize and soybean production (Lobell *et al.*, 2013, 2014; Jin et al., 2016), the water use efficiency of maize–soybean rotation system (Dietzel *et al.*, 2016) and environmental aspects of cropping systems (Martinez-Feria *et al.*, 2016). During the course, researchers have started to calibrate and validate crop, soil and environmental modules included in the APSIM platform such as soil temperature, moisture and nitrogen dynamics for the Midwestern USA (Archontoulis *et al.*, 2014a; Dietzel *et al.*, 2016) and have accumulated a set of parameterized maize and soybean cultivars in this region (Archontoulis *et al.*, 2014a,b). In this study, the APSIM version 7.7 was used for both crops.

Quantify the impacts of heat and drought stresses

In APSIM, heat and drought stress can cause yield losses through its effects on crop phenological (life cycle), morphological (leaf development and senescence) and physiological processes (photosynthesis and grain formation), as well as soil water and nitrogen processes that supply water and nitrogen to the plants. The effect of drought and heat stress on root growth is captured in the model as both soil moisture and temperature affect the rate of root front velocity and therefore supply of water to plants. The feedbacks among these processes are complex and hard to coordinate (Parent & Tardieu, 2014). Therefore, in this study, we only focus on the direct impact of heat and drought stress on maize and soybean production.

As the start point of grain yield modeling, daily biomass accumulation (ΔB) in APSIM is calculated as the minimum of light (ΔB_r)- and water (ΔB_w)-limited photosynthesis. The light-limited biomass production based on the concept of radiation use efficiency (RUE) is calculated:

$$\Delta B_r = I \times \mathrm{RUE} \times \min\{f_{T,\mathrm{photo}}, f_{N,\mathrm{photo}}\}, \tag{1}$$

where I ($\mathrm{MJ\,m^{-2}}$) is the solar radiation intercepted by the canopy, RUE ($\mathrm{g\,MJ^{-1}}$) is a crop-specific, stage-dependent coefficient that converts radiation to dry matter, and $f_{T,\mathrm{photo}}$ and $f_{N,\mathrm{photo}}$ are temperature and nitrogen stresses on photosynthesis, respectively. The temperature stress, $f_{T,\mathrm{photo}}$, is a trilinear function of the daily mean temperature:

$$f_{T,\mathrm{photo}} = \begin{cases} 0, & \text{otherwise} \\ 1 - \frac{T_{\mathrm{opt1}} - T_{\mathrm{mean}}}{T_{\mathrm{opt1}} - T_{\mathrm{min}}}, & \text{if } T_{\mathrm{min}} < T_{\mathrm{mean}} < T_{\mathrm{opt1}} \\ 1, & \text{if } T_{\mathrm{opt1}} < T_{\mathrm{mean}} < T_{\mathrm{opt2}} \\ \frac{T_{\mathrm{max}} - T_{\mathrm{mean}}}{T_{\mathrm{max}} - T_{\mathrm{opt2}}}, & \text{if } T_{\mathrm{opt2}} < T_{\mathrm{mean}} < T_{\mathrm{max}} \end{cases} \tag{2}$$

in which parameter values for the US Midwest based on literature review (Prasad *et al.*, 2008; Schlenker & Roberts, 2009; Parent & Tardieu, 2014; Eyshi Rezaei *et al.*, 2015; Jin *et al.*, 2016) are [T_{min}, T_{opt1}, T_{opt2}, T_{max}] = [8, 15, 29, 44] for maize and [T_{min}, T_{opt1}, T_{opt2}, T_{max}] = [10, 20, 30, 40] for soybean. The water-limited biomass production is calculated as:

$$\Delta B_w = \Delta B_r \times \min\left\{\frac{W_s}{W_d}, 1\right\}, \tag{3}$$

where W_s is the potential daily soil water uptake through the multi-layer soil profile and W_d is the transpiration water demand calculated as the ratio of ΔB_r ($\mathrm{gC{\cdot}m^{-2}}$) and TE ($\mathrm{gC\ m^{-2}\ mm^{-1}}$). TE is determined by the VPD and a crop-specific transpiration efficiency coefficient (TE_c):

$$\mathrm{TE} = \frac{\mathrm{TE}_c}{\mathrm{VPD}}, \tag{4}$$

in which TE_c is a constant of 0.009 KPa for maize and 0.005 KPa for soybean when [CO_2] is 350 ppm (Tanner & Sinclair, 1983). As the calculation of VPD is temperature dependent, a strong interaction between temperature and water stress exists in the model structure. Similarly, APSIM calculates N stress on crop growth using a supply/demand approach; for more details, we refer to Keating *et al.* (2003) and Archontoulis *et al.* (2014a).

The grain yield production is then estimated based on the dry matter supply (i.e., biomass allocation) and demand (determined by the kernel number and kernel filling rate) for maize, and the harvest index (HI) for soybean (Robertson *et al.*, 2002). In the Maize module, the average rate of crop growth (which can be affected by heat, water and nitrogen stresses) during the critical period between flag leaf (around tasseling) and start grain filling sets the actual number of kernels per ear (Edmeades & Daynard, 1979). Excessive heat (>38 °C) reduces the kernel number in proportion to the accumulated degree-days during the flowering phase (Carberry *et al.*, 1989). Once the crop enters the effective grain filling period, high temperature can slow down the kernel filling rate if it exceeds 30 °C (i.e., optimum for grain filling rate). The kernel filling rate is further reduced by nitrogen stress and a soil water stress factor ($f_{\mathrm{SW,kernel}}$), in which:

$$f_{\mathrm{SW,kernel}} = 0.45 + 0.55 \times \min\left\{\frac{W_s}{W_d}, 1\right\}. \tag{5}$$

For soybean, the daily potential increase in HI is adjusted by an energy cost to synthesize the oilseeds but not any direct heat stress. In this study, we add a stress factor (f_{HSA}) to account for the impact of heat stress during the flowering period on the HI following Deryng *et al.* (2014):

$$f_{\mathrm{HSA}} = \frac{1}{\mathrm{TSP}}\sum_{1}^{\mathrm{TSP}} f_{\mathrm{HSA}d}, \tag{6}$$

where TSP is the thermal sensitive period from $\min\{0.45\,\mathrm{GPL}, \mathrm{flowering}\}$ to $\max\{0.7\,\mathrm{GPL}, \mathrm{flowering}\}$ and GPL is growing period length defined as emergence to maturity; the daily heat stress scalar, $f_{\mathrm{HSA}d}$, is calculated as:

$$f_{\mathrm{HSA}d} = \begin{cases} 1, & \text{if } T_{\mathrm{eff}} < T_{\mathrm{cr}} \\ 1 - \frac{T_{\mathrm{eff}} - T_{\mathrm{cr}}}{T_{\mathrm{lim}} - T_{\mathrm{cr}}}, & \text{if } T_{\mathrm{cr}} \le T_{\mathrm{eff}} < T_{\mathrm{lim}} \\ 0, & \text{if } T_{\mathrm{eff}} > T_{\mathrm{lim}} \end{cases} \tag{7}$$

in which T_{cr} and T_{lim} a 35 and 40 °C, respectively and T_{eff} is the daytime effective temperature approximated by the average of daily mean and maximum air temperature.

To estimate contributions of heat and drought stress to yield losses, we regrouped three major stresses and introduce three switches to control the inclusion of each group (Table 1). A specific group of stress is disabled from the simulation routine if the switch value set to 0 and enabled when the switch value equals 1. Details about the implementation of these switches are given in the Text S1. We denote $Y(S_T = S_H = S_D = 1)$ as the simulated yield when all stresses are enabled (i.e., the default APSIM simulation) and $Y(S_T = S_H = S_D = 0)$ as the simulated yield without any of the aforementioned stresses. Based on our experience with the APSIM model structure, we assumed that there is no interaction between heat and the other two stresses; disabled temperature stress may exacerbate drought stress, because it increases potential biomass production and hence the water demand. The impact of temperature stress on yield (denoted as $dY(S_T)$) can be calculated as:

$$dY(S_T) = \frac{Y(S_T = 1, S_H = S_D = 0) - Y(S_T = S_H = S_D = 0)}{Y(S_T = S_H = S_D = 0)}. \tag{8}$$

Similarly, we calculated the heat ($dY(S_H)$) and drought ($dY(S_D)$) stress impact as:

$$dY(S_H) = \frac{Y(S_T = 0, S_H = 1, S_D = 0) - Y(S_T = S_H = S_D = 0)}{Y(S_T = S_H = S_D = 0)} \tag{9}$$

$$dY(S_D) = \frac{Y(S_T = S_H = S_D = 1) - Y(S_T = S_H = 1, S_D = 0)}{Y(S_T = S_H = S_D = 0)}. \tag{10}$$

The interaction between temperature and drought ($dY(S_{T\times D})$) stress was quantified as:

$$\begin{aligned} dY(S_{T\times D}) &= dY(S_T) - \frac{Y(S_T=S_H=S_D=1) - Y(S_T=0, S_H=S_D=1)}{Y(S_T=S_H=S_D=0)} \\ &= \frac{Y(S_T=S_H=0, S_D=1) - Y(S_T=S_H=S_D=0)}{Y(S_T=S_H=S_D=0)} - dY(S_D) \end{aligned}. \tag{11}$$

And the total climatic yield gap due to climate extremes was:

$$\begin{aligned} & dY(S_T) + dY(S_H) + dY(S_D) \\ & = \frac{Y(S_T = S_H = S_D = 1) - Y(S_T = S_H = S_D = 0)}{Y(S_T = S_H = S_D = 0)}. \end{aligned} \tag{12}$$

Inclusion of additional stress switches for phenology and morphology (e.g., leaf appearance and senescence) was not considered in this study.

Table 1 Three switches added to the Agricultural Production Systems Simulator platform to control the inclusion and exclusion of various stresses in the crop simulation routines

Stress	Switch	Functionality
Temperature	S_T	Regulates the inclusion of higher-than-optimum temperature stress that reduces the RUE of both crops and the kernel filling rate of maize
Heat	S_H	Regulates the inclusion of heat stress around the flowering phase, which imposes restriction on the development of maize kernel number and soybean HI
Drought	S_D	Regulates the inclusion of drought stress on RUE of both crops and the kernel filling of maize

For each switch, the corresponding stress is enabled if the switch value is set to 1 and disabled if the value equals 0. The switches affect only the high-temperature part of the stress factors (see Text S1 for a graphical representation).

Simulate maize and soybean responses to elevated CO_2

The observed mean [CO_2] for the period of 1995–2004 is 370 ppm, and the projected mean [CO_2] for 2085–2094 is 534 ppm under the representative concentration pathway 4.5 (RCP4.5) scenario (Wise *et al.*, 2009) and 845 ppm under RCP8.5 (Riahi *et al.*, 2007). To mimic the effects of elevated [CO_2] in our simulation, we adjusted the maize transpiration efficiency coefficient to 0.0092 KPa for 1995–2004, 0.0108 KPa for the RCP4.5 scenario and 0.0137 KPa for RCP8.5 based on multiple [CO_2] manipulation studies for C4 crops reported in Lobell *et al.* (2015). The magnitude of change approximately equals 10.6% increase per 100 ppm. We did not change RUE for maize, because as a C4 crop, its photosynthesis is already CO_2 saturated at current [CO_2] level (Leakey *et al.*, 2006); thus, elevated [CO_2] likely has very little direct stimulation on maize RUE (Long *et al.*, 2006). For soybean, we used the multi-year averaged values from soybean FACE experiment (SoyFACE; Bernacchi *et al.*, 2005, 2007) to derive TE_c and RUE for 1995–2004 and by 2090 under RCP4.5, because the CO_2 manipulation of 550 ppm at SoyFACE is very close to the CO_2 value of 534 ppm by 2090. In this case, TE_c and RUE are 0.0051 KPa and 0.898 g MJ^{-1} for 1995–2004, respectively. For the RCP4.5 scenario, TE_c increases by 10.2% from the 350 ppm CO_2 level to 0.00551 KPa and RUE increases by 18.4% to 1.04 g MJ^{-1}. For the RCP8.5 scenario, we extrapolated values based on multiple enclosure experiments that have raised CO_2 level closer to the projected value of 845 ppm (Table 2). Because TE_c and RUE are not directly measured by most of the FACE and enclosure studies, we derived the values from two conceptually similar measures that are available from the literature. Specifically, we approximated the percentage change in stomatal conductance to water vapor (g_s) for TE_c and changes in the light-saturated leaf photosynthesis rate (A_{sat}) for RUE (see *Discussion* for justification). In this case, TE_c increases by 37.6% to 0.0069 KPa and RUE increases by 39% to 1.22 g MJ^{-1}.

APSIM regional simulations

We conducted the point-based APSIM simulation for both rainfed maize and soybean at a spatial resolution of 10 km for two contrasting time slices: (i) 1995–2004, and (ii) 2085–2094 (under the RCP4.5 and the RCP8.5 scenarios, respectively). Geographic distributions of rainfed maize and soybean are derived from the 5 arc minute (approximately 10 km) resolution MIRCA2000 data set (Portmann *et al*., 2010). The rainfed crop grids were extracted based on two criteria: (i) crop covers more than 2% of the grid area, and (ii) for mixed grids, the rainfed area should be two times more than the irrigated area. In total, we obtain 26 220 grids for maize and 26 651 grids for soybean (Fig. S1).

Meteorological inputs for the APSIM include daily maximum and minimum temperature, daily precipitation and solar radiation. For the historical period of 1995–2004, we used data from the Daymet Web site (http://daymet.ornl.gov/), which was resampled to 10-km resolution by averaging all Daymet pixels fall into each 10-km grid. Future climate scenarios were first generated by a 12-km regional climate model (WRF versions 3.3.1) and then linearly interpolated into 10-km resolution. The initial and boundary conditions for WRF were collected from three different global climate models (GCMs) from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) archive (Wang & Kotamarthi, 2015; Zobel *et al*., under review). These are Community Climate System Model, version 4 (CCSM4), Geophysical Fluid Dynamics Laboratory Earth System Model with Generalized Ocean Layer Dynamics component (GFDL-ESG2G) and the Hadley Centre Global Environment Model, version 2-Earth System (HadGEM2-ES). These three GCMs are carefully selected to capture the spread of changes in global mean temperature in response to a doubling CO_2 projected by all CMIP5 models. We named the WRF simulations as WRF-CCSM4, WRF-GFDL and WRF-HadGEM hereafter. Climate projections by individual WRF simulations under the RCP4.5 and RCP8.5 scenarios are given in Figs S3 and S4, respectively.

Soil parameters for the entire USA, such as soil texture, layered soil hydraulic properties and soil organic matter fractions, were extracted from the 1 : 250 000 (i.e., the minimal area delineated is approximately 10 km^2) US General Soil Map (STATSGO2) database. The description for each of these required soil parameters for APSIM is documented in Archontoulis *et al*. (2014a). For a given grid, it may cover multiple soil map units according to STATSGO2, and each map unit normally contains more than one component that stores layer-specific soil parameters. To balance the computational cost and soil heterogeneity, we only considered soil map units that cover more than 5% of each grid, and the largest component within each soil map unit. When doing the simulation, our script will run APSIM for each of major soil map units and calculate the area weighted average yield for the grid.

Management information such as seeding rates and fertilizer amount to maize for the historical period of 1995–2004 was taken from the USDA National Agricultural Statistics Service (NASS) survey report at state level. Crop sowing date was derived from the Crop Calendar Dataset (Sacks *et al*., 2010). We used site-specific cultivar information and not one cultivar for all locations. Spatial distribution of maize hybrids was assigned based on the decadal average growing degree-days (GDD), and the distribution of soybean cultivar was assigned based on the latitude (Table S1). Then, we utilized generic maize hybrids (from 80 to 125 day relative maturity) and soybean varieties (from 00 to V maturity group) provided

Table 2 Literature reported changes in soybean transpiration efficiency (TE) and radiation use efficiency (RUE) under elevated CO_2

Study	Ambient	Elevated	TE	Scaled TE	RUE	Scaled RUE
Acock *et al*. (1985)	330	800	24%	17.9%	+40%	+29.8%
Jones *et al*. (1985)	330	800	18%	13.4%		
Bunce (1996)	350	700	37%	37%		
Booker *et al*. (1997)	364	726			+56%	+54%
Dugas *et al*. (1997)	359	705	57%	57.7%		
Luo *et al*. (1998)	350	700			+46%	+46%
Serraj *et al*. (1999)	350	700	25%	25%		
Allen *et al*. (2003)	350	700	9%	9%		
Bernacchi *et al*. (2005)	370	550	10%		+18%	
Bunce (2014)	380	560			+28%	

According to the meta-analysis, Ainsworth *et al*. (2002), A_{sat} on average increases by 39% across all [CO_2] treatments and is not significantly affected by [CO_2] level. g_s decreased by 36% at 600–800 ppm and 51% at [CO_2] > 850 ppm. These conclusions can be viewed as an upper limit.
Scaled TE/RUE is values for an increase in CO_2 from 350 to 700 ppm.

by APSIM version 7.7 to run the simulation for each grid. We assumed the same spatial information for future scenarios of 2085–2094 as the baseline simulation, thus excluding the potential of agronomic improvement on crop adaptation and mitigation.

Matching baseline simulation (1995–2004) with county-level yield statistics

Before doing future predictions, we adjusted the management inputs from state to county level for both crops to ensure that the simulated decadal mean yields for years 1995–2004 were comparable to the NASS reported county-level crop yield. The detailed procedure is provided in the supplementary materials (Text S2). For a specific county, we generated several levels of management inputs around the state-level NASS statistics and selected the combination that gives the best yield match as the final inputs. The underpinning assumption is that actual management inputs for each county are within a realistic range of its corresponding state-level NASS statistics. The fertilizer rate, maturity group and seeding rate were allowed to vary by up to ±30%, ±1.5 and ±20%, respectively. Historical yield trend caused by cultivar improvements over time was not considered in our simulations, because the main objective of this study is to assess changes in the impact of climate extremes on decadal-scale crop yield. A recent study on crop model uncertainty propagation (Wallach *et al.*, 2016) suggested that the contribution of model parameter uncertainty is small when evaluating changes in predictions, and averaging over multiple years substantially reduces the prediction errors. Some occasionally occurred damages, such as hail, flooding and pest diseases, were not simulated by the APSIM and thus may cause overestimation of the yield.

Results

Model evaluation at county level

The simulated decadal mean maize yield of 1995–2004 ranges from 3.6 to 10.4 t ha^{-1}, with high yield occurring at some counties from the core Corn Belt and low yield occurring in the northeastern USA (Fig. 1a). For soybean, the simulated yield ranges from 1.55 t ha^{-1} in the US southeast to 4.04 t ha^{-1} at the core Corn Belt. In general, our simulations successfully capture the spatial pattern of NASS reported county-level rainfed maize and soybean yield. The maize simulation slightly outperforms the soybean simulation in capturing the NASS variations ($R^2 = 0.71$ for maize vs. $R^2 = 0.55$ for soybean). For both crops, APSIM simulations overestimate the county-level yield (RMSE = 1.18 t ha^{-1} for maize and RMSE = 0.76 t ha^{-1} for soybean). This overestimation is less for the high yields portion and greater when yields are low and thus is likely because limiting factors such as pest/diseases/hail/floods are not accounted in APSIM and to some extent due to the fact that we used modern cultivars for the entire period of 1995–2004. Because the focus of this study is to assess relative impacts of extreme events on current and future crop yield, the slight overestimation of NASS yield by APSIM would have limited effect on the following analysis.

Projected climate change

In comparison with the period of 1995–2004, decadal mean growing season daily maximum temperature (T_{max}) for the entire region during 2085–2094 is projected to increase by 2.0 °C under RCP4.5 and 3.8 °C under RCP8.5. Warming is most prominent in the US Midwest under both scenarios and thus strikes much of the major maize and soybean planting area (Fig. 2a and b). Projected growing season precipitation (*Prec*) differs slightly between two scenarios for the Midwest (Fig. 2c and d), in which most of the region has either decreased *Prec* up to 100 mm or nominal increase under RCP4.5 but become wetter under RCP8.5. Eastern USA is projected to receive significantly more *Prec* under both the RCP4.5 and the RCP8.5 scenarios. Different climate models in general agree on the spatial pattern of T_{max} under both RCP scenarios, but give distinct projections in terms of the place and the magnitude of additional precipitation (Figs S4 and S5). On regional scales, changes in maximum weekly averaged VPD (maxVPD) are slightly higher under RCP8.5 than under RCP4.5 (0.62 vs. 0.41 kPa). However, the most drastic increases in maxVPD occur at the core Corn Belt states (especially Iowa) under the RCP4.5 scenario, possibly because of the conjugation of warming and moderate drying, whereas for RCP8.5, regions with substantial maxVPD move toward southwest, which could be less detrimental to maize and soybean production. Using median instead of mean of WRF-CCSM4, WRF-GFDL and WRF-HadGEM projections does not significantly change the aforementioned trend (Fig. 2 vs. Fig. S3).

Projected crop yield changes without considering responses to elevated [CO_2]

In response to the projected climate change, maize yield under RCP4.5 decreases mostly by 10–40% in the Midwest where high maxVPD and drying are concurrent (Fig. 3). When comparing simulations forced by individual WRF-GCMs, increased *Prec* in general reduces maize yield loss, while reduced *Prec* exacerbates yield loss (Figs S4 and S6). Maize yield loss under RCP8.5 is greater compared to RCP4.5 over most of the study region (Fig. 3b), even though *Prec* on average is considerably higher in eastern USA under RCP8.5 than under

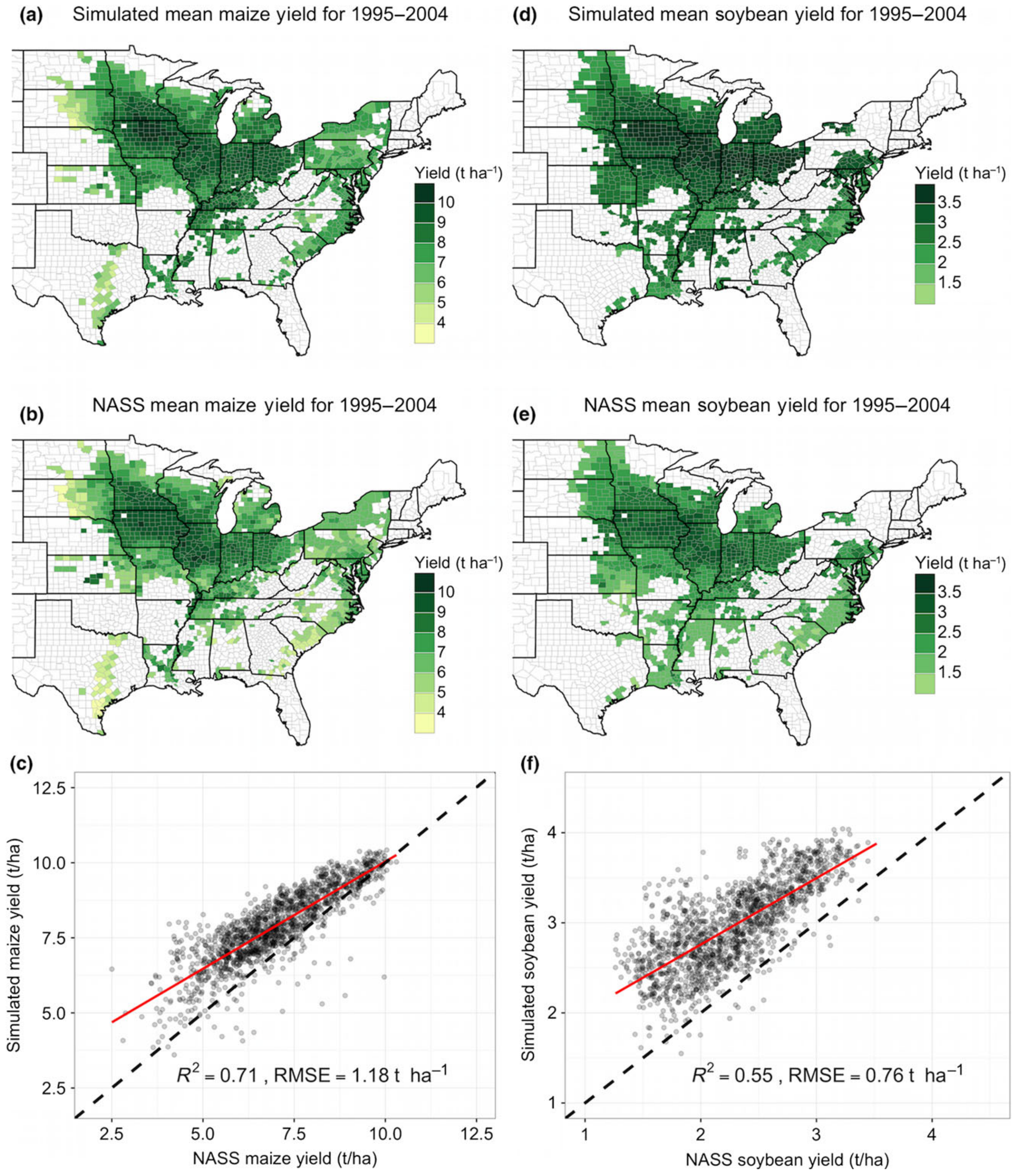

Fig. 1 Validation of Agricultural Production Systems Simulator simulated baseline (1995–2004) decadal mean maize (a, b, c) and soybean (d, e, f) yield against the USDA National Agricultural Statistics Service (NASS) reported rainfed crop yield at county level. Dashed lines are the 1:1 ratio line. Red lines are the linear regression fit. [Colour figure can be viewed at wileyonlinelibrary.com]

RCP4.5 (Fig. 2). We speculate that it is because water supply for eastern USA is currently excessive; thus, extra precipitation will not compensate the loss caused by warming.

Most of the current soybean planting area suffers from yield losses by the late 21st century under both RCP4.5 and RCP8.5 scenarios (Fig. 4a and b). Without considering the CO_2 fertilization effect, yield loss is

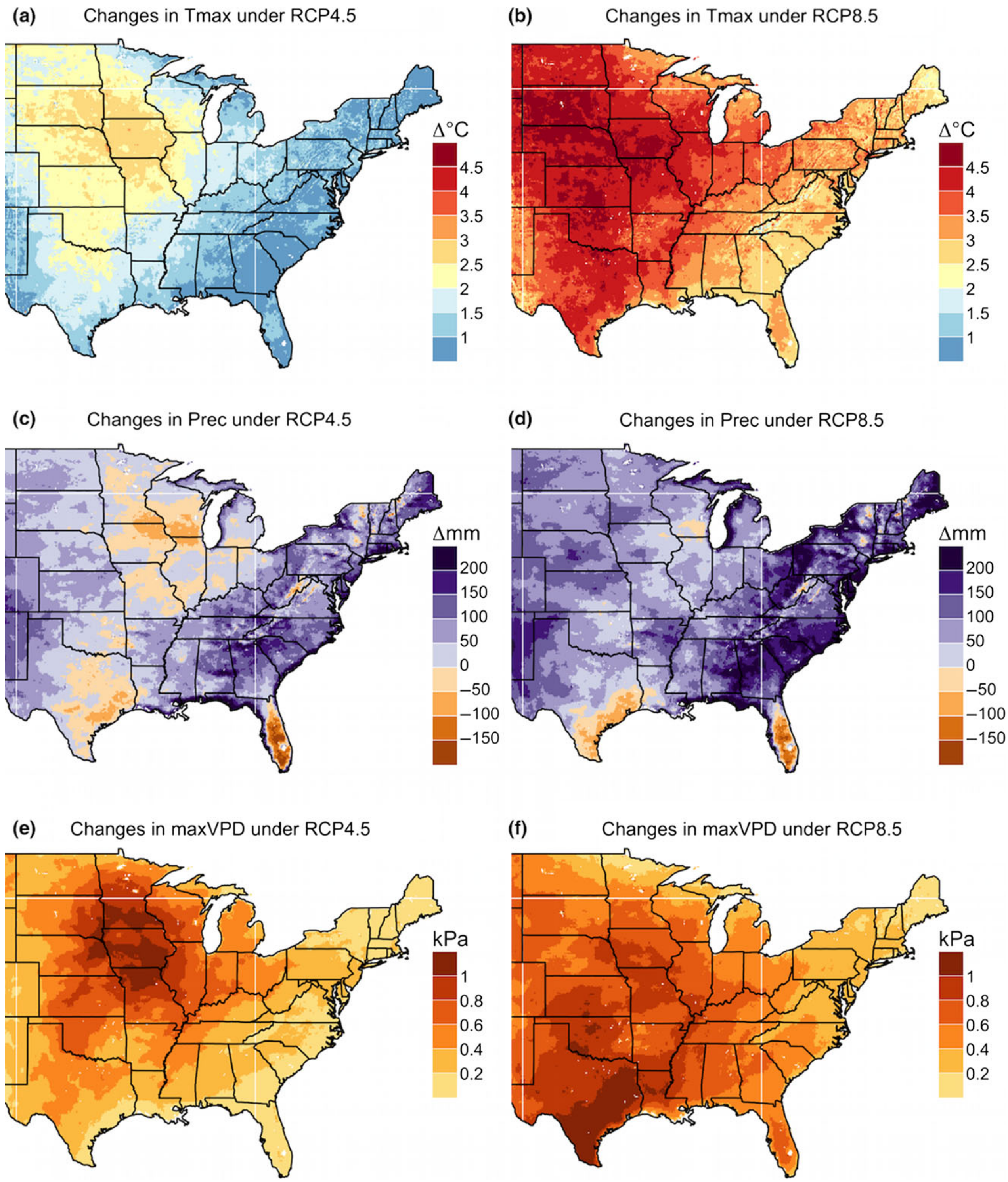

Fig. 2 Changes in the WRF projected decadal mean maximum growing season temperature (T_{max}), cumulative growing season precipitation (*Prec*) and maximum weekly vapor pressure deficit (maxVPD) by the late 21st century (2085–2094) under RCP4.5 and RCP8.5 scenarios compared to the baseline condition of 1995–2004. Each panel reports the mean of WRF-CCSM4, WRF-GFDL and WRF-HadGEM projections. Median values of multiple climate projections are given in Fig. S3. [Colour figure can be viewed at wileyonlinelibrary.com]

higher under RCP8.5 than under RCP4.5 (−33.3% vs. −20.4%). Highest losses in the Midwestern USA generally occur in places where T_{max} and maxVPD increases are high. Noticeably, the southeastern USA experienced severe yield losses under both RCP4.5 and RCP8.5 scenarios. Given the relatively favorable future growth

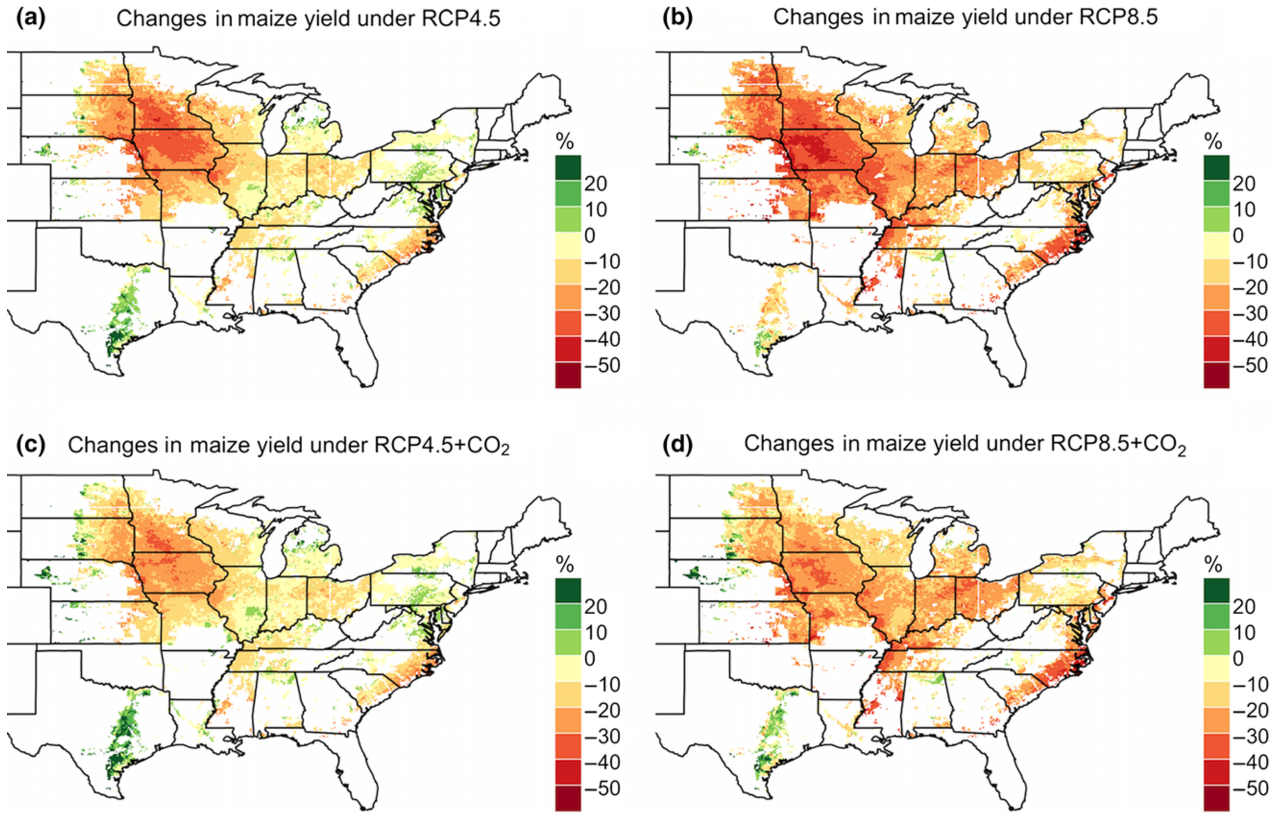

Fig. 3 Agricultural Production Systems Simulator projected changes in decadal mean maize yields of 2085–2094 in comparison with the baseline of 1995–2004, with (a, b) and without (c, d) considering the effect of elevated CO_2 on maize transpiration efficiency. Each panel reports the mean of crop simulations using three different climate projections (Figs S4 and S5). Individual simulations are given in Fig. S6. [Colour figure can be viewed at wileyonlinelibrary.com]

condition in this region (Fig. 2), the projected high yield losses might be a result of mismatch in cultivar or planting date; thus, tuning cultivars and planting dates with future climate change may counterbalance the negative impact (e.g., Vanuytrecht *et al.*, 2016).

Additional precipitation is beneficial to high-loss regions in the Midwest, but seems ineffective for median-loss regions and the southeastern USA (Figs S4, S5 and S7). Without considering the [CO_2] rising, simulations using three different climate models under RCP8.5 all predict yield losses for the Midwest (Fig. S7), indicating that soybean has a different sensitivity to changes in the aforementioned climate variables than maize.

Effects of elevated [CO_2] on yield

For maize, considering the effect of elevated [CO_2] noticeably alleviates yield losses in the western part of the Corn Belt under both RCP scenarios, but only brings very limited benefits for the eastern USA where water condition is favorable and yield loss is small (Fig. 3). This phenomenon is further revealed with the violin plot (Fig. 5), in which the distribution of yield change shrinks at low quantile but is almost the same at high quantile. A possible explanation is that regions with yield gain when excluding the CO_2 effect are not drought-stressed, and hence, CO_2-induced water conservation does not benefit the yield production. This finding is consistent with the empirical evidence that maize has little to gain in the absence of water stress (Leakey *et al.*, 2006). The CO_2 fertilization effect is close between two RCP scenarios (Table S2).

For soybean, the positive effect of elevated [CO_2] on yield is apparent under both RCP scenarios (Fig. 4 and Table S2) and is consistent across all regions and all climate projections (Fig. S7). On average, soybean yield response changes from −20.6% to −10.3% under RCP4.5 and from −33.2% to 4.4% under RCP8.5 after accounting for the CO_2 fertilization effect. Yield responses to elevated [CO_2] are higher for soybean than for maize and are more prominent under the RCP8.5 scenario (Fig. 4). These results were expected because elevated [CO_2] not only increases soybean's canopy transpiration efficiency but also directly stimulates higher than normal photosynthesis rate. The

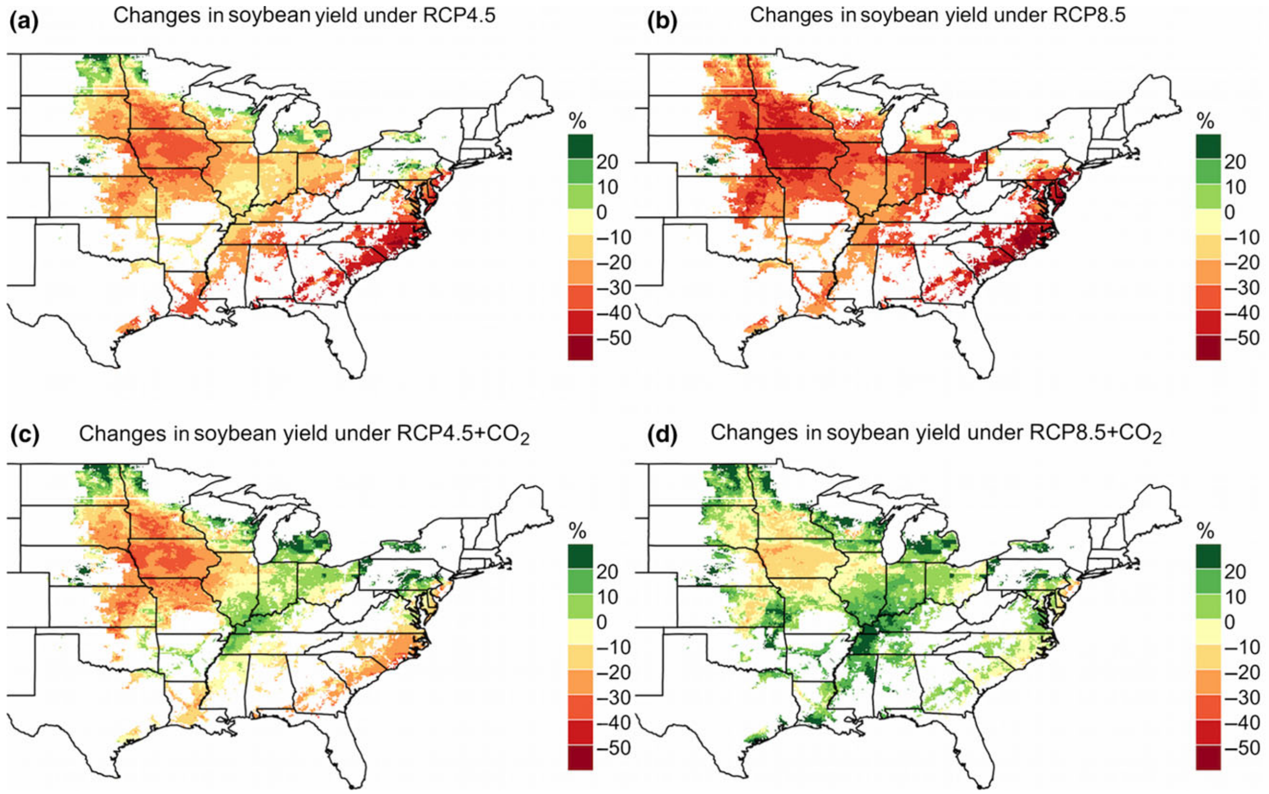

Fig. 4 Agricultural Production Systems Simulator projected changes in decadal mean soybean yields of 2085–2094 in comparison with the baseline of 1995–2004, with (a, b) and without (c, d) considering the effect of elevated CO_2 on maize transpiration efficiency. Each panel reports the mean of crop simulations using three different climate projections (Figs S4 and S5). Individual simulations are given in Fig. S7. [Colour figure can be viewed at wileyonlinelibrary.com]

distribution of yield change under RCP4.5 diverges from the 50% quantile when CO_2 is considered in the simulation, suggesting that the effect of elevated [CO_2] is nonhomogeneous across different quantiles (Fig. 5e and g). In fact, the distribution shrinks more at the lowest quarter, indicating that elevated [CO_2] will benefit regions with high climatic yield gaps more.

Overall, elevated [CO_2] has higher influence under RCP8.5 for both maize and soybean, which is likely because of the much higher [CO_2] level under RCP8.5 than RCP4.5 (845 ppm vs. 534 ppm). After considering the CO_2 fertilization effect, yield losses of both crops are greater in the core production region of the US Midwest than in remaining areas (Figs 4 and 5). Yield responses of both crops are negatively correlated with $T_{\max}$ and maxVPD and positively correlated with *Prec*, with maxVPD also modifying sensitivity to *Prec* (results not shown). The projected sensitivity of yield changes to climate extremes and elevated [CO_2] is comparable to the results from studies that use multiple process-based crop models driven by multiple GCM outputs (Deryng *et al*., 2014; Rosenzweig *et al*., 2014) and to the conclusions from an empirical analysis for the US maize (Urban *et al*., 2015).

Shifts in the influence of heat and drought stresses

For maize, the regional mean climatic yield gap of 1995–2004 derived from the baseline simulation is ~5.2% and can be almost fully attributed to drought (Fig. 6a). By the late 21st century, the mean climatic yield gap increases substantially to 12.5% under RCP4.5 and 14.9% under RCP8.5. Including the CO_2 fertilization effect into simulations markedly reduces the climatic yield gap, mainly through the alleviation of drought stress (Fig. 6b). Drought remains the dominant stress under RCP4.5, while temperature stress stands out under RCP8.5. One noticeable feature of the change under the RCP8.5 scenario with CO_2 effect included is that $dY(S_T)$ and $dY(S_H)$ in total account for 88% of the yield gap (Fig. 6b), thus indicating that agronomic adaptation and mitigation strategies will need to focus more on high temperature and heat stress. The interaction term of $dY(S_{T\times D})$ is less than half of $dY(S_T)$ under the RCP8.5 scenario, suggesting that the negative impact on yield caused by higher temperature cannot be fully compensated via CO_2-induced water conservation.

Similar to maize, the baseline simulation for soybean gives a climatic yield gap of 8.1% and is dominated by

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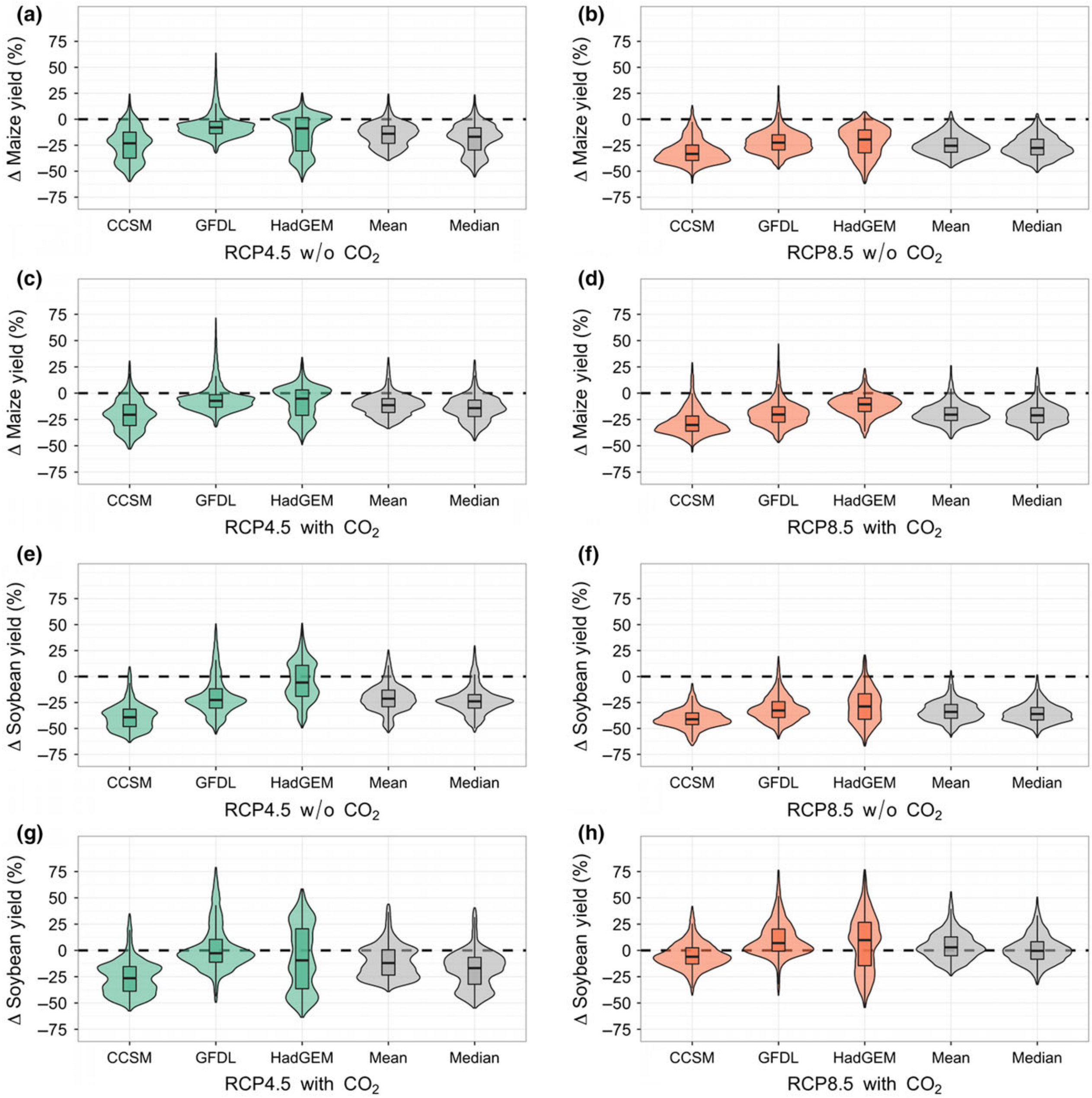

Fig. 5 Violin plot of changes in the decadal mean maize (a–d) and soybean (e–h) yield of 2085–2094 in comparison with the baseline period of 1995–2004 with and without considering the effect of elevated CO_2. Gray color represents the ensemble mean and median of simulations with multiple climate projections. [Colour figure can be viewed at wileyonlinelibrary.com]

$dY(S_D)$ as well (Fig. 6c). Over the time, the projected yield gap increases slightly to 16.0% under RCP4.5 and 21.4% under RCP8.5, among which drought remains its dominant role under the RCP4.5 scenario. $dy(S_T)$ and $dY(S_H)$ combined are responsible for less than one-third of total climatic yield gap under RCP4.5, but contribute to more than 50% under RCP8.5 (Fig. 6c). In contrast to maize, considering the CO_2 effect does not lower the relative importance of drought stress for soybean, but instead increases the drought fraction under both scenarios (Fig. 6d). We believe this is because drought, compared to high temperature and heat stress, not only directly offsets the benefit of higher transpiration efficiency for soybean, but also limits the benefit from CO_2-stimulated RUE when high water demand is not satisfied.

By using generalized additive model (GAM) fitting, we identify that the interaction between temperature

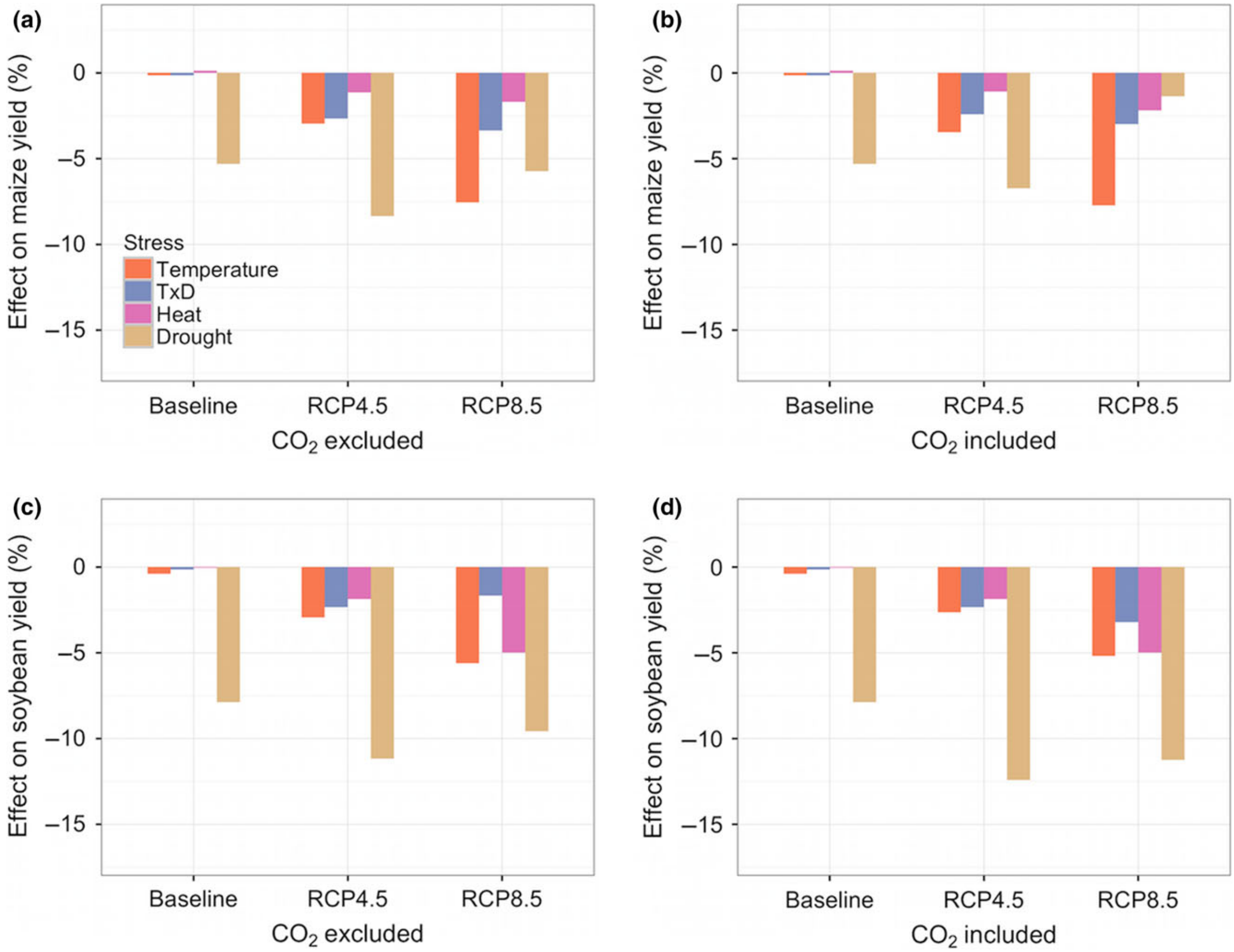

Fig. 6 Partitioning the impacts of climate extremes on yields into high temperature, heat and drought stresses for maize (a, b) and soybean (c, d) under multiple climate scenarios with and without considering the effect of elevated CO_2. Results are the ensemble means of Agricultural Production Systems Simulator simulations driven by three WRF-GCM climate projections. $T \times D$ is the interaction between temperature and drought stress derived from Eqn. 11. [Colour figure can be viewed at wileyonlinelibrary.com]

and drought stress ($dy(S_{T\times D})$) tends to be higher under high VPD quantile for both crops, irrespective of climate scenarios or the inclusion of CO_2 into the simulation (Fig. S8). In general, including the CO_2 effect reduces $dY(S_{T\times D})$ of maize, but slightly increases the magnitude of interactions of soybean.

On top of yield gaps due to climate extremes that directly stress the photosynthesis and reproductive processes, it should be mentioned that warming could hasten the crop growth cycle and shorten both the vegetative and reproductive phase. In particular, the average maize grain filling day drops by 15% under RCP4.5 and 25% under RCP8.5; the average soybean filling days reduces by nearly 8% under both climate scenarios (Fig. 7). The relatively lower change in soybean reproductive length compared to maize is most likely due to photoperiod that affects phase duration in soybeans and possibly due to different thermal requirements between crops (optimal temperature for the phenological thermal time accumulation is 34 °C for maize and 30 °C for soybean) and leaf senescence rates.

Given that the shift of different stresses may not be uniform across the region, and the potential implications for breeding and variety selection, we further investigate the spatiotemporal dynamics in the geographic distribution of climatic stresses on potential crop yields (Fig. 8). The baseline simulation for maize suggests that climatic stresses of more than 5% mainly occur in the west of the US Midwest and is almost purely in the form of drought (Fig. 8a). In response to climate change, areas that exhibit yield gaps of more than 5% expand, especially in the core Corn Belt and the eastern USA. A mixture of $dY(S_T)$ and $dY(S_D)$ is

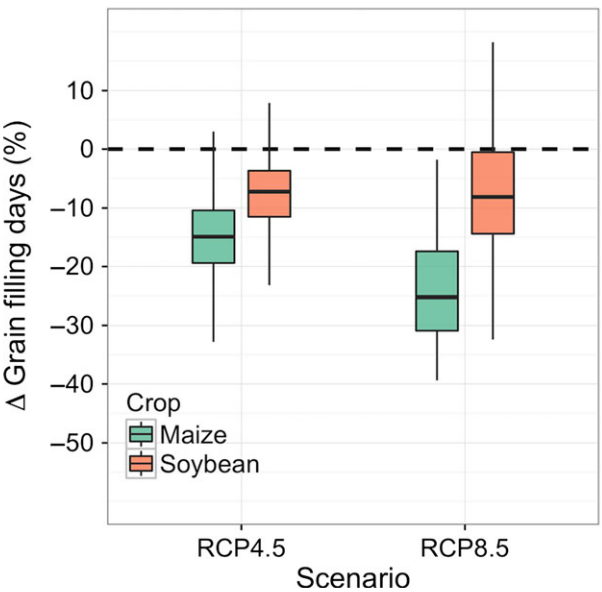

Fig. 7 Changes in the number of maize and soybean reproductive days. [Colour figure can be viewed at wileyonlinelibrary.com]

identified in the western part under RCP4.5 (Fig. 8b), while $dY(S_T)$, instead of $dY(S_D)$, becomes more pervasive in the southern and eastern USA under RCP8.5 (Fig. 8c). Simulations with the CO_2 effect included project falling of the drought stress, in particular under RCP8.5 (Fig. 8d and e).

For soybean, droughts dominate all over the study region for the baseline period (Fig. 8f). Future climate change under the RCP4.5 scenario leads to expanded stresses in the northern part of the US Midwest (Fig. 8g and i), where warming and drying concur (Fig. 2). Temperature and/or heat stress take over the role of drought in most of the southern USA (Fig. 8h and j). Including the CO_2 effect has little influences on the spatial dominance of different stresses under both RCP4.5 and RCP8.5. Future projections also reveal a consistent spatial pattern of the geographic distribution of different stresses, that is: $dY(S_T)$ dominant in the southeastern USA, $dY(S_H)$ dominant in the western part of study area, and $dY(S_D)$ dominant in the north, with mixtures of stresses lie in between (Fig. 8).

Discussion

By using the very-high-resolution downscaled climate projections from multiple GCMs and a modified version of APSIM, this study quantifies yield responses of US rainfed maize and soybean to future climate extremes by the late 21st century and for the first time characterizes spatial aspects of the relative importance of temperature, heat and drought stress in this region. We demonstrate that future climatic yield gaps of maize and soybean are greatest in the US Midwest under both RCP4.5 and RCP8.5 scenarios. The effect of elevated CO_2 will partially but not completely offset yield losses caused by climate extremes, and this effect is more prominent in soybean than in maize. Our results show that drought will continue to be the largest threat to maize and soybean production in this region, although its dominant role may gradually give way to the other two stresses in response to the combination of rising CO_2 and associated climate changes. We also reveal that shifts in the geographic distributions of the stress dominance are characterized by the increases in the concurrent stresses, especially for the core Corn Belt. Collectively our findings suggest the importance of considering drought and extreme heat simultaneously for future agronomic adaptation and mitigation strategies, particularly for breeding programs and crop management.

Spatial variability in climate stress

Yield responses to future climate extremes are not unidirectional in this region. Maize and soybean yield losses are greater in the US Midwest, where lower precipitation, higher temperature and higher VPD are projected to co-occur. Drought is the dominant stress in these regions; therefore, the corresponding yield losses can be effectively alleviated by elevated [CO_2] in the future. For the southeastern and eastern USA, where current and future precipitation is likely to be excessive, elevated [CO_2] brings little benefit to maize. This suggests the importance of considering hydroclimatic thresholds. A recent systems modeling analysis for a typical research farm in the US Midwest showed that the optimal water use efficiency for maize occurred with 430 mm seasonal rainfall, whereas yields did not benefit from additional precipitation above these levels (Dietzel *et al.*, 2016). The exact precipitation threshold may vary from one place to another, as a result of interactions with other climatic and edaphic factors. Our analysis of the spatial pattern of stress dominance (Fig. 8) can be viewed as an early attempt to qualitatively identify spatial heterogeneities in the vulnerability of the regional cropping systems. Given that the risks of extreme heat and drought depend not only on the severity of the event *per se* but also on the sensitivity and vulnerability of the exposure system, more detailed quantitative assessments are needed in the future.

Future climate extremes are likely to strike crop growth as concurrent heat and drought events, thus setting higher demand for agricultural adaptations as the optimal breeding or management strategy may differ among stresses (Lobell *et al.*, 2015). A number of crop

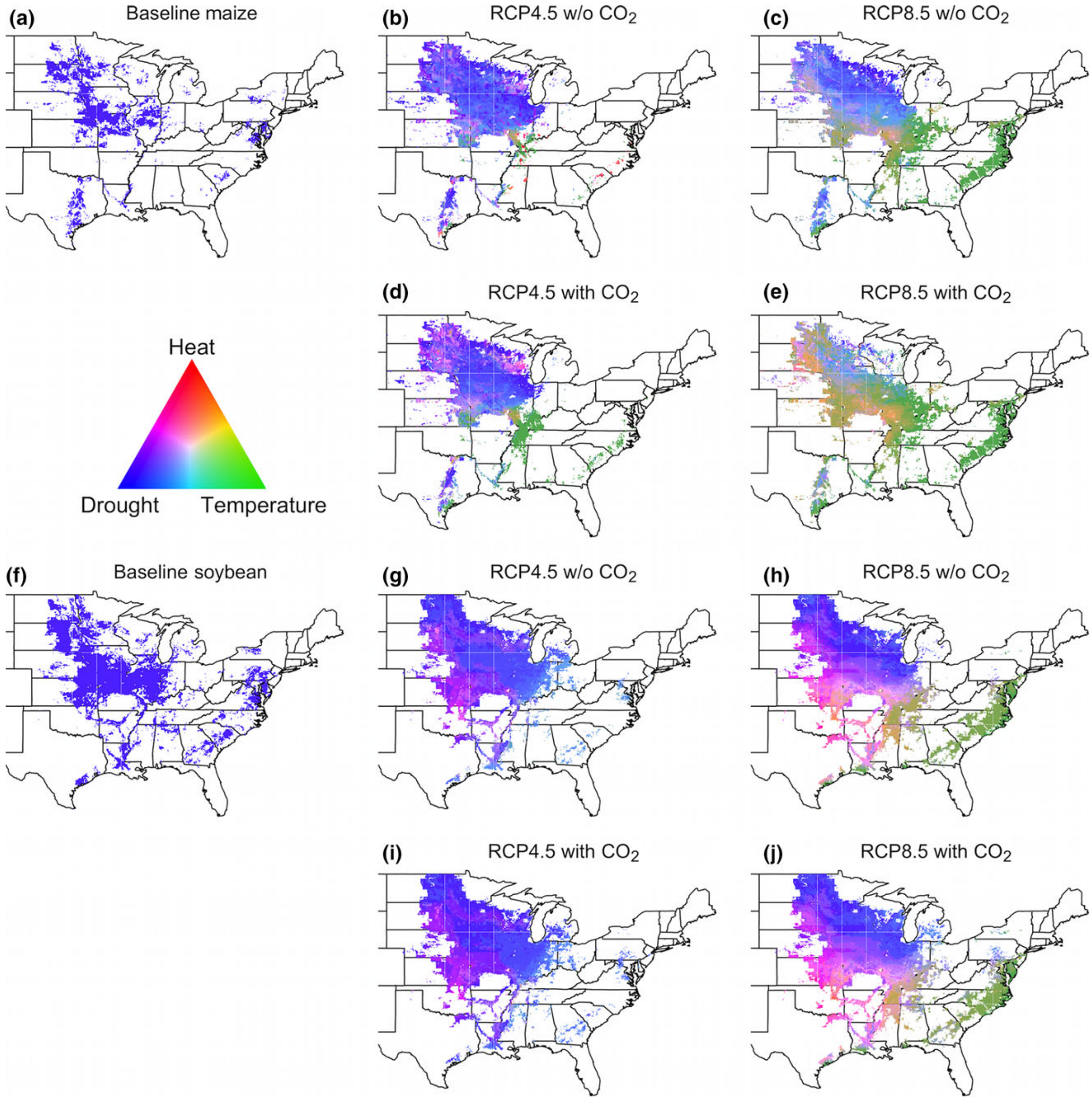

Fig. 8 Projected shifts in the geographic distribution of relative importance of high temperature, heat and drought stresses on maize (a–e) and soybean (f–j) yields under multiple climate scenarios with and without considering the effect of elevated CO_2. Only grid cells with more than 5% climatic yield gaps are shown in the plots. [Colour figure can be viewed at wileyonlinelibrary.com]

traits can be potentially adopted to ameliorate drought stress, including the limited-transpiration trait that can stabilize or even lower transpiration rates of both maize and soybean under high VPD conditions (Sinclair *et al.*, 2010; Messina *et al.*, 2015; Shekoofa *et al.*, 2016). Yet limiting transpiration may bring the side effect of enhancing temperature stress, as canopy transpiration is a major pathway for latent heat flux. For example, Messina *et al.* (2015) showed that the benefit of limited-transpiration trait was more prominent for drought-prone environments, while yield penalty was simulated for wet conditions. In addition, our simulations for both maize and soybean show that increasing heat tolerance may not necessarily be a positive action for arid environment, because it may exacerbate drought stress as a result of higher biomass production and higher water demand. The net effect depends on the magnitude of interactions between temperature and drought stress and is likely affected by VPD as is shown in Fig. S8. The trade-off between drought tolerance and heat tolerance for breeding programs may vary with geographic locations and deserve more research efforts. Simulation studies will continue to provide valuable references to find the optimal strategy. However, more detailed understanding needs to be incorporated into the current generation of crop models to achieve this (Hammer *et al.*, 2010; Boote *et al.*, 2013).

Uncertainties from climate projections

It should be noted that the climate forcing data are one major but inevitable source of uncertainty in the projections presented as is the case for many other crop modeling studies (Asseng *et al.*, 2013; Ruane *et al.*, 2013; Deryng *et al.*, 2014; Vanuytrecht *et al.*, 2014). The use of WRF downscaled climate scenarios that capture more detailed spatiotemporal climate variability (Wang & Kotamarthi, 2015) allows us to assess the climate change impact on maize and soybean yields at a county level. However, it may amplify the uncertainty from GCM outputs that provide the boundary conditions for the WRF simulation. While climate model projections generally agree with the direction and magnitude of temperature changes, they are less concordant in precipitation change (IPCC, 2013). In our case, because of different precipitation regimes (Figs S4 and S5) among WRF-GCMs, simulated yield responses with different climate projections are distinct under both RCP 4.5 and RCP8.5. Using any one specific climate model thus could lead to contradictory conclusions (for example, Figs S6 and S7). However, the tremendous computational cost of dynamical downscaling is currently the major obstacle for the inclusion of larger number of climate models for analyses. In this study, we conduct the WRF simulation and projection driven by three different GCMs including CCSM4, GFDL-ESM2G and HadGEM2-ES. As presented by Sherwood *et al.* (2014), the ultimate change in global mean temperature in response to a doubling of atmospheric CO_2 in CMIP5 models spans roughly 2.1–4.6. Among more than 30 GCMs, GFDL-ESM2G is one of those models which have very low responses to the increase in CO_2, with global mean temperature increasing by 2.38 °C, while HadGEM2-ES is one of two models that have the highest response to the doubling of CO_2, with global mean temperature increasing by 4.55 °C. CCSM4 shows a response which is in between above two models, with global mean temperature increasing by 2.92 °C. This captures the range of responses of the climate models to RCP scenarios without doing every model in between. However, it should be noted that using three GCMs, although better than one, still might have not provided representative projections. Employing a multi-model ensemble of Regional Climate Models (RCMs) could give better representativeness than using WRF alone (Vanuytrecht *et al.*, 2014).

Uncertainties from crop model parameterization

The projected compensations of elevated [CO_2] to stress-induced yield losses highly depend on the parameterization of crop physiological responses (i.e., changes in TE and/or RUE in response to elevated [CO_2]). Uncertainty may be less for maize than for soybean, because elevated [CO_2] primarily affects TE of C4 crops yet substantially affects both TE and RUE of C3 species (whose effects may counteract each other). For example, a recent study based on eight-year SoyFACE experiments showed that the water saving effect of higher TE on soybean could be offset by greater LAI as a consequence of stimulated RUE under the rising [CO_2], and hence, elevated [CO_2] does not always protect soybean from drought stress (Gray *et al.*, 2016). Moreover, unlike the general agreement on maize TE (Lobell *et al.*, 2015), the response of soybean TE and RUE to elevated [CO_2] is far less consistent among different studies (Ainsworth *et al.*, 2002). SoyFACE often predicted much more conservative soybean physiological responses than enclosure experiments (Long *et al.*, 2006; Ainsworth *et al.*, 2008), possibly because enclosure experiments were not able to realistically reproduce the soil–plant–atmosphere continuum (Long *et al.*, 2006). For both crops, however, none of the current FACE has manipulated CO_2 level close to the scenario of RCP8.5 (>800 ppm) at the late 21st century, making the parameterization much more uncertain under high emission scenarios.

The rising land surface ozone concentration ([O_3]) further complicates the quantification of CO_2 fertilization effect. O_3 is a global threat to crops (Long *et al.*, 2005; Mills *et al.*, 2007; Tai *et al.*, 2014) and has reduced the US rainfed maize and soybean yields by ~10% and 5%, respectively, based on historical observations since the 1980s (McGrath *et al.*, 2015). Elevated [CO_2] may partially offset the negative effect of high [O_3] exposure (Long *et al.*, 2005; Ainsworth *et al.*, 2012), but cannot prevent O_3-induced accelerated leaf senescence that lowers canopy light interception and reduces crop yield (Dermody *et al.*, 2008). Therefore, our projection of yield gain from the rising [CO_2] is prone to overestimation by excluding the O_3 effect. The magnitude of O_3 damage varies with crops and environmental conditions (Ainsworth *et al.*, 2012). Yield sensitivity to elevated O_3 is generally considered to be less for the maize than soybean, given the intrinsically lower stomatal conductance of C4 crops (McKee *et al*., 2000; Mills *et al*., 2007), but is likely to be higher for the US rainfed maize than soybean (McGrath *et al*., 2015). The projected drought relief as a result of higher transpiration efficiency noted here may be diminished if the O_3 effect was included. There is evidence showing that exposure to high [O_3] impairs the functioning of abscisic acid (ABA) signaling (one critical mechanism that regulates the stomatal response to soil drying and changes in VPD), thus causing continued water loss despite the possibility of crop dehydration (Wilkinson & Davies, 2010). ABA signaling also interacts with temperature (Wilkinson & Davies, 2010) and partially explains the observed exacerbation of O_3 damage by high temperatures (Tai *et al*., 2014; McGrath *et al*., 2015). Representing these complex interactions in crop models is still in a nascent stage. The impacts of elevated O_3 on tulip polar can be reasonably simulated with the community land model (CLM) by directly modifying the maximum rate of carboxylation and stomatal conductance in a coupled Farquhar/Ball-Berry model (Lombardozzi *et al*., 2012). This version of CLM was later parameterized for all plant functional types and used to assess the global carbon and water cycles in response to chronic ozone exposure (Lombardozzi *et al*., 2015). Similar approach can be applied to crop models that are built on the concept of RUE (e.g., APSIM), such that parameters of RUE and TE are dynamically reduced according to the cumulative O_3 exposure metrics. However, the parameterization of either stomatal or RUE-based models at crop species level is currently restricted by the progress in high-quality experimental data.

The projections derived in this study using APSIM may overstate the benefit of higher TEc, because it does not explicitly simulate the canopy energy balance feedback that high TEc reduces transpiration but, meanwhile, causes the canopy temperature to rise, which will likely offset some of the beneficial effect on the water balance. As a result of this negative canopy energy balance feedback, the reduction in canopy transpiration is often smaller than the magnitude of reduction in stomatal conductance, with greater differences observed in soybean than in maize (Boote *et al*., 2013). In this study, we approximate the percentage change in g_s as the change in TE_c mostly because a direct measure of TE_c is unavailable in most enclosure or FACE experiments. The more often reported change in canopy transpiration is not equal to the change in TE_c, as the transpiration calculated in APSIM also depends on VPD. While most crop models do not include the canopy energy balance or feedbacks, due to the complexity involved, simpler approaches may be appropriate for future model improvement (Boote *et al*., 2013). A recent study on multi-model comparison of simulating canopy temperature suggested that empirical algorithms performed as well as more comprehensive mechanistic algorithms in their ability to reproduce the crop canopy temperature (Webber *et al*., 2015). These empirical algorithms are often easy to implement, although their parameters need to be localized when applied to a novel region.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Text S1. Implementation of stress switches.
Text S2. Procedure for determining county-level management inputs based on NASS state-level statistics.
Table S1. Criteria for assigning maize and soybean generic cultivars.
Table S2. Regional mean maize and soybean yield responses under different climate scenarios in comparison to the baseline period of 1995–2004.
Figure S1. Maximum monthly area fractions of US rainfed maize and soybean for each 5 arcmin grid around 2000.
Figure S2. Decadal mean growing season growing degree days (GDD) between April 1st to September 30th of 1995–2004.
Figure S3. Changes in the WRF projected decadal mean maximum growing season temperature (T_{max}), cumulative growing season precipitation (*Prec*) and maximum weekly vapor pressure deficit (maxVPD) by the late 21st century (2085–2094) under RCP4.5 and RCP8.5 scenarios compared to the baseline condition of 1995–2004.
Figure S4. Decadal mean maximum temperature (T_{max}) during the growing season (May 1st to Sep 30th), cumulative growing season precipitation (*Prec*) and maximum weekly vapor pressure deficit (VPD) of 2085-2094 projected by WRF that uses CCSM4 (a, d, g), GFDL-ESG2G (b, e, h) and HadGEM2-ES (e, f, i) outputs under RCP4.5 as initial and boundary conditions.
Figure S5. Decadal mean maximum temperature (T_{max}) during the growing season (May 1st to Sep 30th), cumulative growing season precipitation (*Prec*) and maximum weekly vapor pressure deficit (VPD) of 2085-2094 projected by WRF that uses CCSM4 (a, d, g), GFDL-ESG2G (b, e, h) and HadGEM2-ES (e, f, i) outputs under RCP8.5 as initial and boundary conditions.
Figure S6. Projected decadal mean maize yield response of 2085-2094 relative to the simulated baseline condition of 1995–2004 with and without considering CO_2 fertilization effect.
Figure S7. Projected decadal mean soybean yield response of 2085–2094 relative to the simulated baseline condition of 1995–2004 with and without considering CO_2 fertilization effect.
Figure S8. Simulated interactions between temperature and drought stress of maize (a–d) and soybean (e–h) given different vapor pressure deficit (VPD) quantiles.