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Assessing climate adaptation options and uncertainties for cereal systems in West Africa

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ABSTRACT

In the coming decades, the already fragile agricultural system in West Africa will face further challenges in meeting food security, both from increasing population and from the impacts of climate change. Optimal prioritization of adaptation investments requires the assessment of various possible adaptation options and their uncertainties; successful adaptations of agriculture to climate change should not only help farmers deal with current climate risks, but also reduce negative (or enhance positive) impacts associated with climate change using robust climate projections. Here, we use two well-validated crop models (APSIM v7.5 and SARRA-H v3.2) and an ensemble of downscaled climate forcing from the CMIP5 models to assess five possible and realistic adaptation options for the production of the staple crop sorghum (*Sorghum bicolor Moench.*): (i) late sowing, (ii) intensification of seeding density and fertilizer use, (iii) increasing cultivars' thermal time requirement, (iv) water harvesting, and (v) increasing resilience to heat stress during the flowering period. We adopt a new assessment framework to account for both the impacts of proposed adaptation options in the historical climate and their ability to reduce the impacts of future climate change, and we also consider changes in both mean yield and inter-annual yield variability. We target the future period of 2031–2060 for the "business-as-usual" scenario (RCP8.5), and compare with the historical period of 1961–1990. Our results reveal that most proposed "adaptation options" are not more beneficial in the future than in the historical climate (−12% to +4% in mean yield), so that they do not really reduce the climate change impacts. Increased temperature resilience during the grain number formation period is the main adaptation that emerges (+4.5%). Intensification of fertilizer inputs can dramatically benefit yields in the historical/current climate (+50%), but does not reduce negative climate change impacts except in scenarios with substantial rainfall increases. Water harvesting contributes to a small benefit in the current climate (+1.5% to +4.0%) but has little additional benefit under climate change. Our analysis of uncertainties arising from crop model differences (conditioned on the used model versions) and various climate model projections provide insights on how to further constrain uncertainties for assessing future climate adaptation options.

1. Introduction

West Africa faces great challenges in reaching food security in the coming decades. The population increase in West African countries will remain among the fastest in the world (United Nation, 2015), adding a large increase in food demands in countries where a large fraction of the population is still facing chronic hunger and malnutrition (Schmidhuber and Tubiello, 2007). Whether the region can meet a growing food demand is further complicated by climate change, which is projected to adversely affect crop yields

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in the future (Lobell et al., 2014, 2011, 2008; Müller et al., 2011; Schlenker and Lobell, 2010; Sultan et al., 2014, 2013). Successful adaptation of agriculture to climate change is key to meet the increasing food demands in this region.

Climate models largely agree on several aspects of future rainfall and temperature changes in West Africa (Biasutti and Sobel, 2009; Biasutti, 2013; Sultan et al., 2014). Higher temperature is expected over the whole West Africa, with a mean warming of 2.8 °C in the decades of 2031–2060 compared to the baseline of 1961–1990 (Fig. 1) for the "business-as-usual" scenario. The projected change in rainfall is more complicated and regionally dependent, with the West Sahel experiencing a delayed rainy season and an overall decrease in total rainfall amount, and the Central Sahel largely experiencing an increase in total rainfall amount (Fig. 1). These climatic changes are superimposed on top of high natural variability in seasonal rainfall, which historically has produced large inter-annual variations in rainfall and prolonged droughts (Giannini et al., 2008) and the recent increase in rainfall intensity and extreme heavy-rainfall events (Panthou et al., 2014). Both climate variability and trend pose a challenge for the primarily rain-fed agriculture systems in West Africa. Any successful adaptations should be able to cope with the short-term climate variability as well as reduce the negative impacts of climate change in the long term (Lobell, 2014; Saba et al., 2013).

Various possible adaptations for crop production have been proposed or assessed in the literature, whether related to technology, management or some combination of the two (Fisher et al., 2015). Major options include changes in crop cultivars and types (e.g. Sultan et al., 2014), improved drought and heat tolerance (e.g. Rosegrant et al., 2014; Singh et al., 2014), changes in sowing rules that shift the crop growth period (e.g. Kucharik, 2008; Lobell et al., 2012; Rosenzweig and Parry, 1994), water harvesting (e.g. Rockström and Falkenmark, 2015; Rosegrant et al., 2014) and irrigation (e.g. Rosenzweig and Parry, 1994), no-tillage (e.g. Derpsch et al., 2010), and intensification with higher planting density and/or higher fertilizer inputs, as was done during the Green Revolution (e.g. Aune and Bationo, 2008; Pingali, 2012). In the case of West Africa and nearby regions, a few adaptation options have been assessed so far through either modeling (Kassie et al., 2015; Singh et al., 2014) or experimental studies (Traore et al., 2014). However, it still remains largely unknown what possible adaptations can best enhance the resilience of crop yield in the current climate as well as be adaptive to the long-term climate change.

A key distinction in defining the benefits of adaptation is made between actions that are generally beneficial to future welfare, and those that specifically reduce the impact of climate change. Our study will adopt the "impact-reducing" definition by Lobell (2014), and use his proposed framework (Fig. 2a) to quantify the true adaptation impact—as well as the impact in the current climate—of a specific adaptation option. The details for the framework and assessment criteria are provided in the Methods.

Here we use two well-validated crop models and an ensemble of downscaled climate forcing from the Climate Model Intercomparison Project, Phase 5 (CMIP5) ensemble to assess a suite of possible adaptations for the production of sorghum [Sroghum bicolor (L.) Moench] in West Africa. Sorghum is the most important cereal in the Guinea and Sudan savannah, where annual rainfall is a mere 600–1100 mm per year (Kouressy et al., 2008). This work expands on a previous impact study for the same region (Sultan et al., 2014), which identified a robust negative impact of climate change on sorghum yield and suggested that switching from the traditional to the modern cultivar is an adaptation. The current work takes a further step to assess a full suite of possible adaptations and attempts to provide guidance for prioritizing adaptation investments. We are addressing the following two questions: (1) What are the adaptation options that can both benefit farmers in the current climate and reduce impacts of climate change? (2) What causes the uncertainties of the various adaptation impacts?

2. Materials and methods

2.1. Crop models and study sites

This study focuses on the regional crop yield response in West Africa (18°W–5°W in longitude and 10°N–18°N in latitude). Detailed meteorological records from 35 stations across the region for the 1961–1990 period have been compiled by AGRHYMET Regional Center and National Meteorological Agencies. For the crop simulation we focused on 13 out of the 35 stations (Fig. 1), because these 13 stations are more evenly distributed across the study area and the aggregated results are less biased to a specific region but rather representative of the whole West Africa pattern.

Two different crop models are used in this study: SARRA-H (version v3.2) (Kouressy et al., 2008) and APSIM (version 7.5) (Hammer et al., 2010; Holzworth et al., 2014). Both models have been calibrated with the same field trial data (Dingkuhn et al., 2008; Traoré et al., 2011). They have also been validated against regional crop statistics from FAO country-level statistics, with the inter-annual correlation coefficient between simulated and observed detrended yields being 0.70 for the SARRA-H model and 0.52 for the APSIM simulations (Sultan et al., 2014). Both crop models simulate soil water balance, plant carbon assimilation, biomass partition and phenology, with APSIM having the major distinctions in (i) explicitly simulating nitrogen stress, (ii) heat stress for grain number formation, and (iii) including the CO_2 fertilization effect. It is worth noting that the recent SARRA-H model has incorporated advanced functionality to include nitrogen cycle and CO_2 fertilization effect, however here we only report the results with the SARRA-H version v3.2 since this was the version that we had when we conducted this research. The heat stress for grain number formation in APSIM happens before (150 GDD units) and shortly (50 GDD units) after the flowering period, and the formation of grain number linearly decreases with daily maximum temperature increasing from 36 °C to 40 °C (Singh et al., 2015). The CO_2 fertilization in APSIM is realized through linearly increasing the transpiration efficiency (i.e. reducing the potential daily water demand associated with a given level of potential photosynthesis) by 37% at 700 ppm compared with at 350 ppm based on the synthesis of multiple field and laboratory studies (Harrison et al., 2014; Lobell et al., 2015). The direct effect of CO_2 on radiation use efficiency is not simulated. These three unique features of APSIM lead to some differences from SARRA-H in their simulated yield response under climate change; this source of uncertainty will be discussed in Section 4. We use the calibrated soil parameters derived from the previous work in Sultan et al. (2014) for the study area. Specifically, due to the low quality of soil survey data for this region, we calibrated the soil parameters (hydraulic properties and soil organic matter) so that (1) our two crop models could simulate the relationship between historical yield and rainfall when driving with historical climate data; and (2) our two crop models could simulate the correct magnitude of yield response at different levels of fertilizer inputs (van der Velde et al., 2014).

2.2. Downscaled and bias-corrected climate forcing

We used historical simulations and the RCP8.5 projections from 8 general circulation models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012), namely CCSM4, CMCC-CM, CMCC-CMS, CSIRO-Mk3-6-0, HadGEM2-ES, IPSL-CM5A-LR, MIROC5, MPI-ESM-Mr. The choice of the models was based solely on the availability of daily values of precipitation and of mean, maximum, and minimum surface

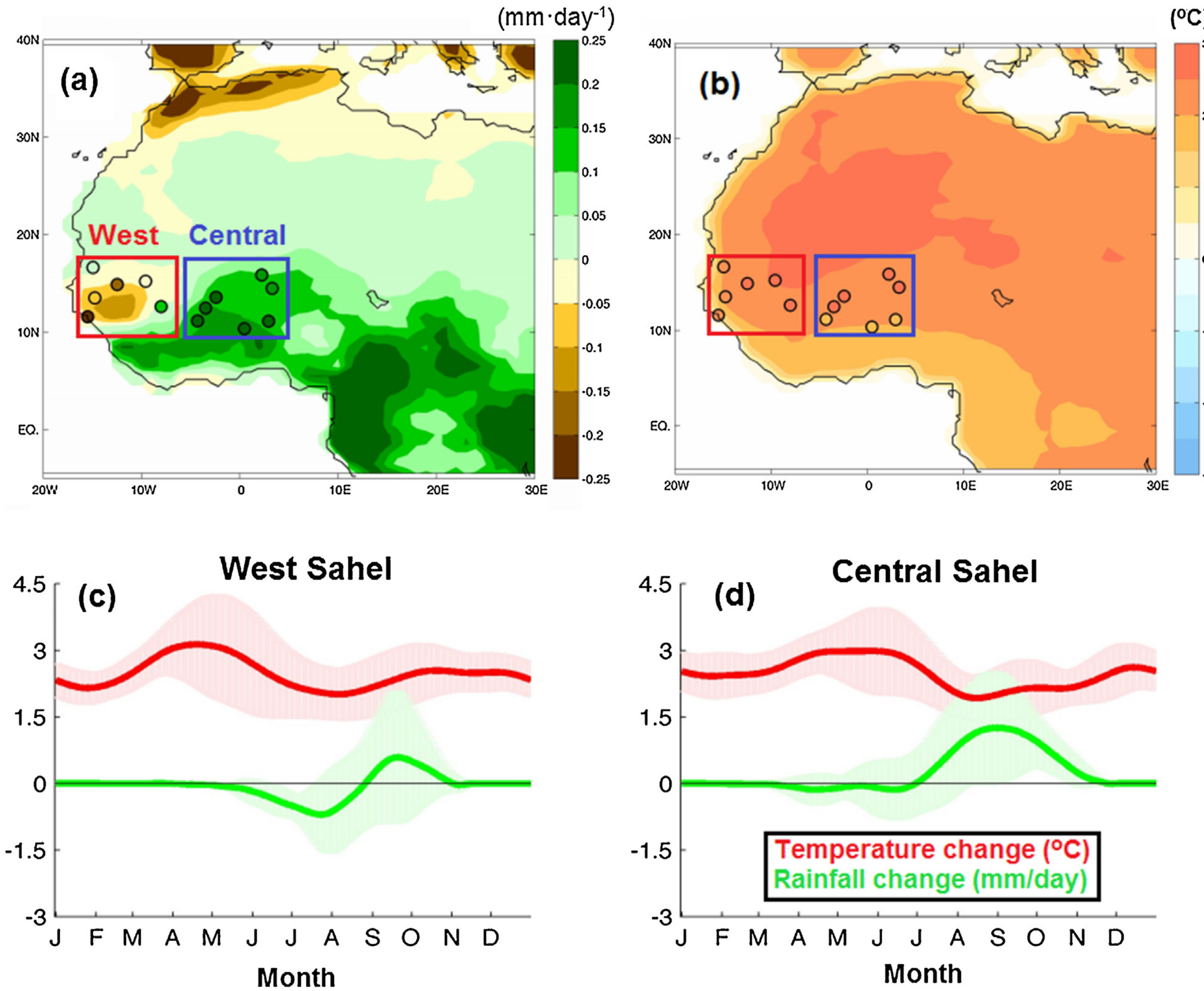

Fig. 1. (a) Multi-model averaged, annual mean rainfall anomalies (in mm day^{-1}) between future and past (2031–2060 in the RCP8.5 scenario and 1960–1990 in the Historical scenario), averaged over 8 climate models. Field values are the anomalies in the raw model output (regridded to 1° resolution). Filled circles are anomalies in the bias-corrected output (see Section 2.2). The boxes indicate the sites of West Sahel and Central Sahel. (b) As in (a), but for temperature in °C. (c) Smoothed daily anomalies in rainfall (mm/day, green) and temperature (°C, red) averaged over the sites of West Sahel. The solid line is the multi-model mean, the shading represents one standard deviation scatter. (d) As in (c), but for the sites of Central Sahel. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

temperature at the time of the study. We focus on the RCP8.5 scenario primarily because we target at a near-term future period (2031–2060) that "business-as-usual" is a reasonable assumption. The ensemble mean change simulated by these 8 models over Western Africa is similar to that of the larger ensemble of all CMIP5 models (Biasutti, 2013; Sultan et al., 2014). We downscaled and bias-corrected these 8 CMIP5 models separately for each month for temperature and precipitation using the meteorological records from the previously mentioned 35 stations, following a method adapted from Piani et al. (2009) and detailed in Sultan et al. (2014). The bias correction is based on a fitted histogram equalization function for daily data and it is linear for temperature, and either linear or a combination of linear and exponential functions for rainfall. We pooled data from all 35 stations to create the observational record of daily rainfall histograms, so that the downscaled time series are representative of the region, but not of any specific location. Moreover, the a priori choice of the functional form for the fit, while insuring objectivity and avoiding overfitting, means that the correction is not perfect, nor it is uniform across models. The main advantage of the bias correction for rainfall is that it simultaneously adjusts the number of dry days (to overcome the drizzle problem of climate models) and the mean rainfall, but some biases remain (Fig. S8). Other variables (i.e. wind, humidity and radiation) necessary for forcing the crop models were obtained from the historical records of weather stations, based on a conditional resampling to preserve the covariance between these variables and precipitation (Guan et al., 2014). The historical period is defined as 1961–1990, and the future projected period is 2031–2060.

2.3. Adaptation framework and evaluation criteria

Following Lobell (2014), Fig. 2a presents a schematic of crop yield response under historical/current and future climate. The x-axis shows a shift of climate conditions towards a higher level of stress, y-axis refers to the mean crop yields, and a new technology/management (T2) replaces the old one (T1). We are interested in calculating the following two terms: (1) the impact on yields in current (or historical) climate = (A–B)/B, i.e the yield change when applying T2 compared with T1 in the current (or historical) climate; and (2) the impact on yields of adaptation to climate change = [(C–D) – (A–B)]/B, i.e. the difference between the benefits of using T2 instead of T1 in the future climate and the counterpart benefits in the current (or historical) climate. Although many contemporary studies simply calculate (C–B)/B as the adaptation

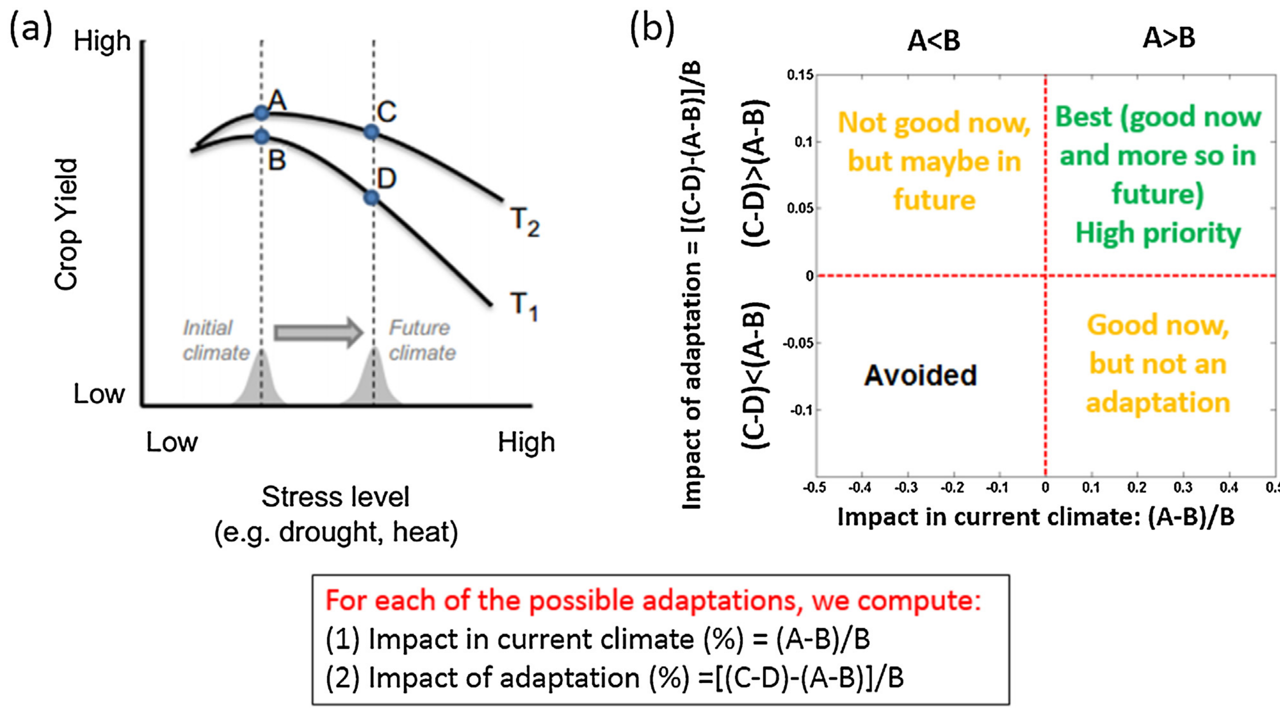

Fig. 2. (a) Diagram of assessing the impacts of different possible adaptation options (technological or managerial, here T1 refers to conventional technology or management, and T2 refers to the new counterpart) under a changing climate (excerpted from Lobell, 2014). (b) Criteria of assessing the priority of various possible adaptation options by considering the impact in the current (or historical) climate (i.e. (A–B)/B) and the impact of adaptation (i.e. [(C–D) – (A–B)]/B).

impact (e.g. Müller et al., 2010; Tao and Zhang, 2010), we argue that using (C–B)/B overestimates the actual adaptation impact. For example, if (C–D) is equal to or smaller than (A–B), the new technology/management (T2) is more beneficial in current climate than in the future, thus T2 does not qualify for the "impact-reducing" definition of adaptation, no matter the sign of (C–B). At the same time, we agree that considering the impact in the current (or historical) climate is necessary as T2 may improve yields and be worth implementing whether or not it qualifies as a true adaptation for climate change.

To summarize, we propose a parsimonious but comprehensive framework to assess different possible adaptation options with regards to the mean yield change (Fig. 2b). The upper-right quadrant, where both the historical/current climate impact and adaptation impact are positive, is the most favorable option; options in the bottom-right quadrant are good for the historical/current climate but do not contribute toward reducing climate change impacts; and options in the bottom-left quadrant are neither good for the current nor the future climate and thus should be avoided. We will use the above framework in our study to assess a suite of possible adaptation options using crop models, with a focus on any options that land in the upper-right quadrant.

2.4. Adaptation options and implementation

Our previous study (Sultan et al., 2014) found that the modern cultivar (shorter height, shorter growing cycle, little photoperiod sensitivity and higher yield ability) is more robust than the traditional cultivar to future climates, on top of providing larger yields in the current climate; thus switching from traditional to modern cultivar is a robust adaptation and we will not assess this option again here. The five possible adaptation options addressed in this study are listed below, with a brief rationale for each of them.

(a) A more conservative sowing rule, which would push toward later sowings to possibly adjust to the projected delay of rainy season onset and also possibly take advantage of the late season rainfall increase;
(b) Intensification with higher planting density and/or with higher fertilizer inputs, to possibly take advantage of increased rain toward end of season (i.e. less risk of running out of water);
(c) Adoption of varieties with longer thermal times, to compensate for the faster development caused by warming. Most genetic variability in sorghum phenology relates to the length of the vegetative stage (Kumar et al., 2009), thus by adjusting the length of the vegetative stage, the total crop growth cycle for the future can be made similar to those in historical climate;
(d) Water harvesting from a certain fraction of runoff, and then irrigation using this stored water during dry spells to possibly reduce the water stress;
(e) Adoption of varieties with increased tolerance to high temperatures during the grain number formation period around flowering, which could counteract the increase in extreme heat occurrence during this time window.

Almost all the above proposed adaptation options can be implemented in a similar fashion in both crop models, though option (e) can only be tested in APSIM as SARRA-H does not incorporate this mechanism. Since our previous study (Sultan et al., 2014) has robustly demonstrated the benefits of modern cultivar over traditional cultivar in both the historical and future climate, we use the modern cultivar in our simulation here (Sim 1–6, see below). The baseline simulation also uses the current management (Sultan et al., 2014), which will be briefly described next. The following experiments are developed:

Sim 1 (baseline): Modern cultivar + Current management.

Sim 2: Late sowing.

Sim 3: Intensification (i.e. higher planting density for both models, and/or higher nitrogen inputs for APSIM).

Sim 4: Thermal time increase.
Sim 5: Water harvesting.
Sim 6: Increased temperature resilience of grain number formation (only for APSIM).

"Current management" follows the previous protocol in Sultan et al. (2014) for both models. In particular, the "current management" includes a sowing rule that is primarily based on the onset of rainy season, purely rain-fed, relatively low planting density (APSIM: 7 plants m^{-2}; SARRA-H: 5.5 plants m^{-2}), and with low fertilizer inputs (SARRA-H is calibrated with low fertilizer input trial data, and APSIM uses 10 kg ha^{-1} urea-nitrogen fertilizer). Sim 1 (i.e. baseline simulation) provides point B and D in Fig. 2a.

"Late sowing" is implemented in both models by delaying the sowing window for one month from the previous default sowing window, where the default sowing window is largely determined by the onset of rainy season (Sultan et al., 2014). The sowing rules within the sowing window in the two models remain the same as before. Briefly, SARRA-H determines its sowing date since the first day in the sowing window by checking when the plant-available soil moisture is more than 8 mm and also followed by a 20 day period during which daily crop biomass remains increasing at least 10 out of 20 days. APSIM determines its sowing date as the last day of the first 10 continuous days in the sowing window with total accumulated rainfall of 20 mm and plant-available soil moisture above 10 mm.

Higher planting density for the "Intensification" is implemented by doubling the previous planting density in both models (7–14 plants m^{-2} in APSIM, and 5.5–11 plants m^{-2} in SARRA-H). Meanwhile, we also increase the fertilizer inputs from 10 kg ha^{-1} to 50 kg ha^{-1} (urea-nitrogen) in APSIM for the "Intensification" scenario. Individual impact of higher planting density and higher fertilizer inputs in APSIM have also been separately simulated and analyzed in our results.

"Thermal time increase" is implemented by increasing the growing degree day (GDD) requirements in both models such that the phenological length of the vegetative stage simulated in the future climate remains similar as that simulated in the historical period. Specifically the thermal requirement for vegetative stage (from "End of the juvenile phase" to "Floral initiation") in GDD has been changed from 369 °C days to 420 °C days in APSIM and 400 °C days to 480 °C days in SARRA-H.

There are very few studies that implement "water harvesting" in process-based crop models (e.g. Rosegrant et al., 2014). Here we provide a parsimonious but also close-to-reality approach to simulate the effect of "water harvesting". We collect runoff whenever there is a runoff generation (from the baseline simulation), and we store a certain percentage (we test 30%, 50% and 70% in our study) of runoff in a hypothetical reservoir and assuming the reservoir has infinite storage capacity. When a dry spell happens and also lasts longer than four days and meanwhile there is available harvested water in the reservoir, farmers apply a certain amount from the reservoir (we tested 5 mm, 7.5 mm and 10 mm respectively) as irrigation at the end of the fourth day in the dry spell; in practice, the irrigated water is applied as "extra rainfall" in the new simulation. The irrigation applying scheme (i.e. 4 day waiting period) is based on the average time when water stress starts to happen since the dry spells begins, and the calculation is based on the simulation only in APSIM model (see Fig. S1). In brief, we use the prior simulated runoff from the baseline (e.g. Sim 1) to calculate the amount of harvested water over time; based on the above rule, we retrospectively decide when and how much harvested water is applied as irrigation; to implement, we incorporate these added "irrigation" in the rainfall record to generate a new rainfall forcing which we then use to re-run the crop model to simulate the "water harvesting" effect. Since runoff simulations in the two crop models slightly differ, we create the irrigation scheme for each model separately (Fig. S2).

"Increased temperature resilience of grain number formation" has only been implemented in APSIM as only APSIM has the explicit parameterization of this process. In general, high temperature tends to affect both grain number and weight, with the former process happening during the flowering period and the latter one happening in the grain-filling period. However for sorghum specifically, various experiments found that the predominant impact of heat stress is on grain number (Lobell et al., 2015; Nguyen et al., 2013; Prasad et al., 2008, 2006; Singh et al., 2015), thus we only vary the grain number sensitivity in APSIM while assuming grain weight is not affected by heat stress. In APSIM, by default the grain number formation during the flowering period is linearly decreased on each day from 100% at a daily maximum temperature (Tmax) of 36 °C to 0% at 40 °C (Singh et al., 2015). In the "adaptation" simulation, we halve the rate of this sensitivity such that the grain number formation is linearly decreased by only 50% as Tmax increases from 36 °C to 40 °C. This type of reduced sensitivity has been observed in some varieties in this study area (Singh et al., 2015).

2.5. Simulation and analysis protocols

The two crop models were run using the same downscaled daily climate forcings at 13 sites for the historical period (1961–1990) and future climate scenario (RCP8.5, 2031–2060). This was done for the baseline (Sim 1) and for each proposed adaptation option. For the historical and future climate respectively, we calculated various yield-based variables (mean yield, 30-year yield variability, yield failure percentage, etc.) at the site level, and then aggregated them over the 13 sites. We then calculated the impact in historical (i.e. A–B in Fig. 2a) and future climate (C–D) from all the climate model ensembles (8 GCMs) for each proposed adaptation option. We also aggregated our results in various other ways, e.g. by regions (All stations: 13 sites; West Sahel: 6 sites; Central Sahel: 7 sites) for assessing regional differences, and by each GCM to assess uncertainties related to climate projections.

Metrics to assess inter-annual yield variability include standard deviation (std), coefficient of variation (CV = std/mean), and yield failure rate, all of which were calculated from the time series of the 30-year crop yields. Smaller std or CV corresponds to a lower risk of the proposed adaptation option and should be favored by risk-averse farmers. Variability of yield is sometimes as important as mean yield. For example, a technology improvement can lead to a higher mean yield but may come with the cost of a high inter-annual variability, and when yield failure rate is too high, risk-averse farmers will not adopt it. In our case, the yield failure is defined as the percentage of the years over the 30-year simulation period that annual crop yield is lower than the 20th quantile of the crop yield in the baseline historical simulation (Sim 1, hist), following a similar definition from Hammer et al. (2014). We have also tested other quantile thresholds (i.e. 10th, 30th) to define yield failure and we find the qualitative pattern does not change when using different quantile thresholds. Since APSIM and SARRA-H differ in their absolute simulated yield, we calculate quantile thresholds for each model separately when quantifying their yield failure percentage.

3. Results

3.1. Overall patterns of mean yield changes

Fig. 3 shows the mean yields of different simulations for the historical and future climate (all scaled by the baseline yield in the historical climate) following the diagram in Fig. 2a. The two crop models show differences across various adaptation options. However, one consensus is that both models show West Sahel is

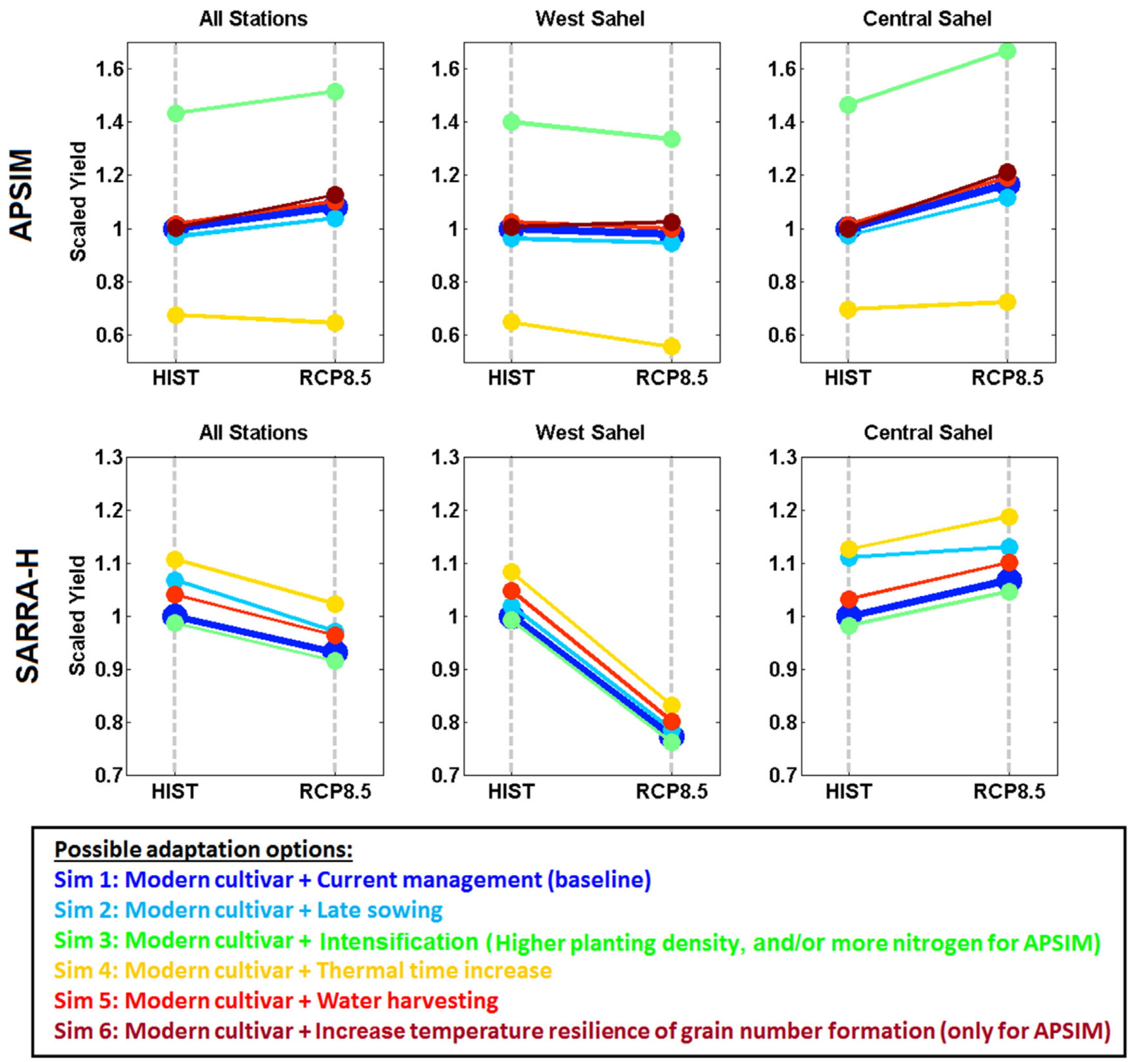

Fig. 3. Simulated mean yield of different possible adaptation options in the historical climate and future climate scenario (RCP8.5) for all stations, stations of West Sahel and stations of Central Sahel, following the diagram Fig. 2(a). All the yield changes have been normalized by the simulated historical yield (Sim 1, i.e. baseline).

in general prone to negative impacts in the future climate for the same adaptation option, while Central Sahel is largely benefited in the future climate. We further calculate the two metrics "impact in historical climate" and "impact of adaptation" (Fig. 2), and use our proposed framework (Fig. 2b) to assess the performance of various proposed adaptation options (Fig. 4). The variations of the region-aggregated results in Fig. 4 comes from the variations in projections across the climate models. For APSIM, we find the following pronounced results: (i) "Intensification" has a significantly positive impact for mean yield (with a median of +52% increase in yield) in historical climate, though it also has a relatively large variation across climate models. (ii) "Thermal time increase" has significantly negative impacts in both historical climate and for adaptation, with large variations in adaptation impact. (iii) "Late sowing" has an insignificantly small negative impact in the historical climate. For SARRA-H, "Late sowing" and "Thermal time increase" both have a positive impact of yield in the historical climate, in contrast to APSIM. The simulated impacts of other proposed adaptation options in the two models are either too small (less than 2%) or not significant (25–75% quantile values includes zero). Next, we will focus on the results for each proposed adaptation option in detail, and aim to gain an understanding of what drives their performance and where their uncertainties come from.

3.2. Sim 2: late sowing

The late sowing effects are relatively small, but the two models have opposite signs in their responses. The impact in the historical climate for APSIM is robustly negative with −2.1% in mean yield for all stations, while the impact of adaptation has larger uncertainties and is not significantly above or below zero. In contrast, SARRA-H shows a positive impact in the historical climate (+6.9% in mean yield for all stations) and a mostly negative impact of adaptation (−2.9% in mean yield for all stations). The divergent pattern between the two models is caused by their simulated phenology, which has been discussed in detail in Guan et al. (2015). In brief, though both models calibrated their phenology with the field data until the flowering phase (Sultan et al., 2014), the lengths for the post-flowering stages in two models were not calibrated and thus are apparently different. APSIM simulates a growing season length of ~114 days in the historical climate, while SARRA-H simulates 90 days in the historical climate, with the major differences for the post-flowering stage. With these differences, a late sowing rule in APSIM leads to 14 days delay in sowing and 10 days delay in harvest, and this delay causes the sorghum growth cycle to extend beyond the end of rainy season and leads to more water stress, which reduces the crop yield (Fig. S3). However, in SARRA-H the

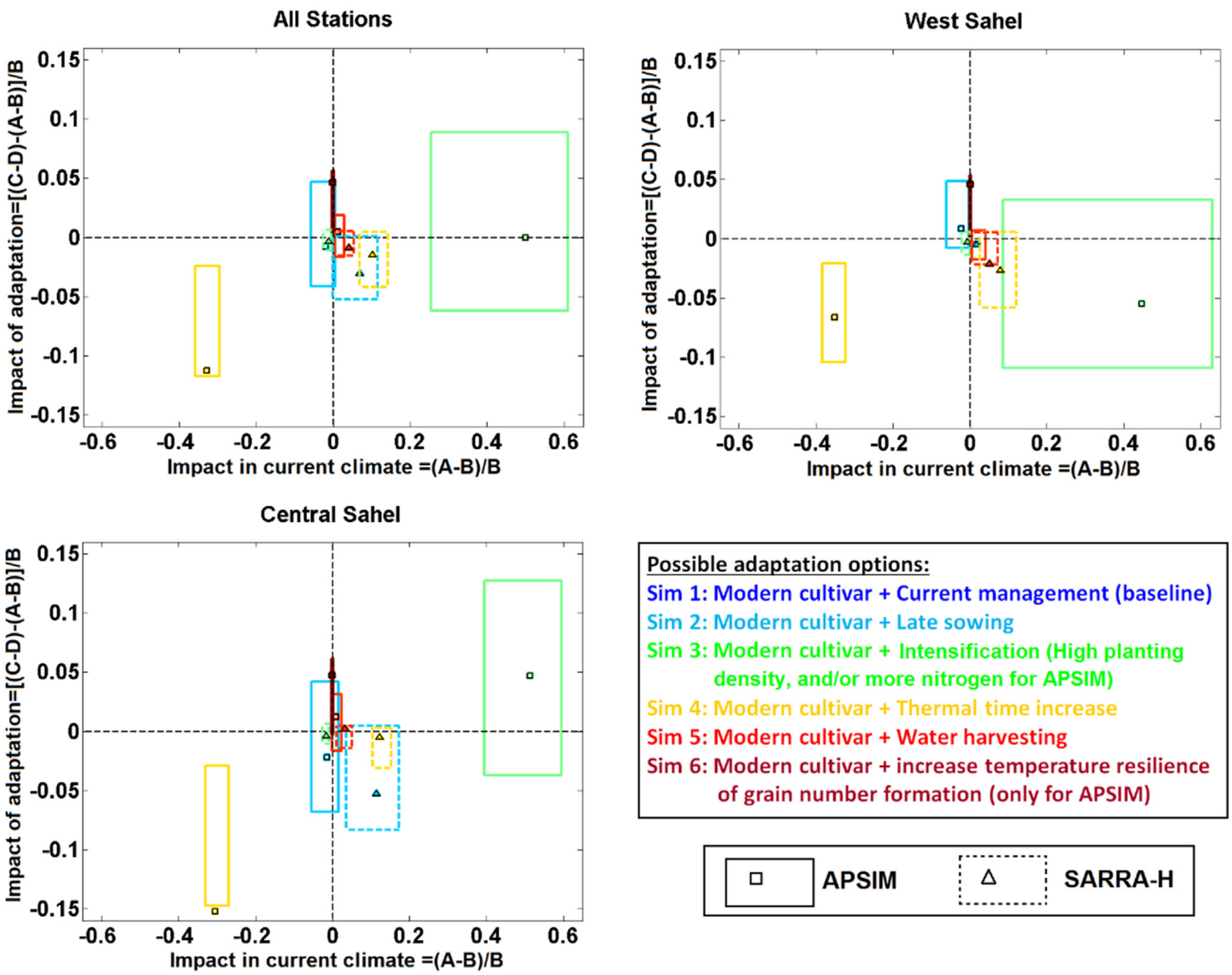

Fig. 4. Assessing the impact of the different proposed adaptation options on the mean yield in the current/historical climate and their impact of adaptation, following the criteria defined in Fig. 2(b). All the yield changes have been normalized by the simulated yield of the baseline (Sim 1). The boundaries of each box shows the 25th and 75th percentile values of the mean yield change of each proposed adaptation option across all the 8 GCMs.

late sowing rule leads to 7 days delay in sowing and 8 days delay in harvest in the historical climate, and this delay puts the SARRA-H simulated growth cycle in a period with more accumulated rainfall and leads to a higher crop yield. Both models show slightly more positive impacts of adaptation of the late sowing effect in West Sahel than in Central Sahel. West Sahel has more clear delays in the seasonal rainfall distribution than Central Sahel, which accounts for the regionally different behaviors in mean yield change.

3.3. *Sim 3: intensification*

Intensification (higher planting density and higher fertilizer input) in APSIM shows a relatively large positive impact in the historical climate (+50% in the mean yield for all stations), but the adaptation impact is not significantly different from zero. SARRA-H (only with higher planting density) does not show significant impacts for either historical climate or adaptation. Excluding the fertilizer impact (i.e. only using 10 kg ha^{-1}) and only having higher planting density in APSIM leads to much smaller impacts, and shows no significant yield increases in the historical climate (Fig. S4d). Thus the large simulated benefits in the historical climate in APSIM is almost exclusively caused by the increased fertilizer use. The low fertilizer case in APSIM is similar to the setup of SARRA-H, which does not explicitly simulate the nitrogen cycle. Thus at low fertilizer inputs, both models show very small responses (<1.0%) with a “higher planting density”.

“Intensification” simulated in APSIM shows large yield variations for both historical climate and adaptation simulations at the site level (Fig. 5). We find that these variations can be largely explained by the mean annual total rainfall. Fig. 5 shows that the impact in historical climate in APSIM has a monotonically increasing trend with the annual total rainfall till ∼1000 mm/year, above which the impact is almost saturated, indicating that crop systems in West Africa can better take advantage of higher fertilizer inputs when water resources are ample, consistent with prior work (e.g. Sultan et al., 2014). The rainfall variations also largely drive the relatively large variations in the simulated impact of adaptation. This also explains why West Sahel is prone to have a negative adaptation impact (−5.8% in mean yield; Fig. 4), while Central Sahel is prone to have a positive adaptation impact (+4.7% in yield; Fig. 4; Figs. S3, S4e–f), because the projected rainfall decreases in West Sahel while it increases in Central Sahel (Fig. 1).

At the low end of rainfall amount, the intensification in APSIM leads to negative yield response (up to −20%, Fig. 5), which mostly results from the increased water stress due to increased planting density (Figs. S3, S4a). Though the impact of higher planting density in SARRA-H is small, the mean impact in historical climate is neg-

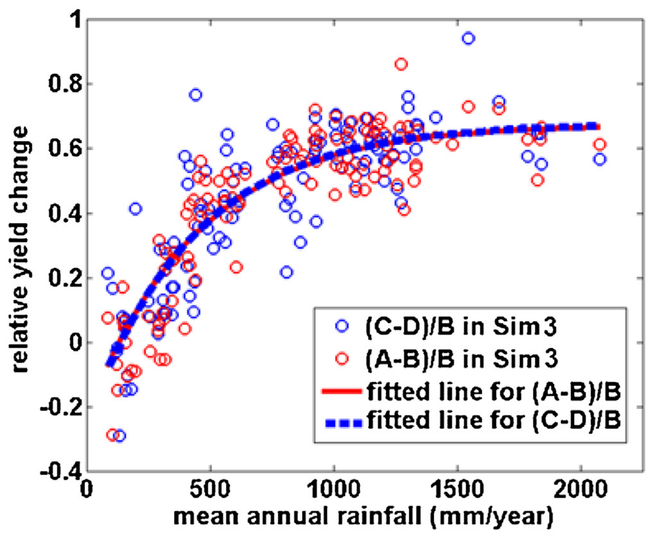

Fig. 5. Yield difference between Sim 3 (higher planting density and higher fertilizer inputs) and Sim 1 (baseline) in APSIM as a function of the mean annual rainfall (averaged over the 13 stations and 8 GCMs). Red dots show the results for the historical/current climate and blue dots show the results for the future climate. We use the function y = a − b × exp(−x/c) to fit the data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

ative (−2.0%, though not significant), and this negative response is also primarily driven by the increased water stress.

3.4. Sim 4: thermal time increase

"Thermal time increase" in APSIM shows significantly negative impacts in historical climate (−33% in mean yield for all stations), whereas this option in SARRA-H shows significantly positive impacts in the historical climate (+11% in mean yield for all stations). Both models show that this option has negative impacts for adaptation (APSIM: −12%, SARRA-H: −1.5%).

We find that though the simulated impact in historical climate and for adaptation in APSIM are both negative, their causes are different. In the historical climate, increasing thermal time (i.e. GDD) of crop elongates crop growing length, and some of crop growth cycles pass beyond the end of rainy season, which leads to more water stress. The increased water stress affects the grain size during the grainfilling period (Fig. 6c), which ultimately causes a yield loss (Fig. 6b). While for the future climate scenario in APSIM, due to the design of the experiment, we make sure that growing season length is the same as that in the historical climate in the baseline. Because the rainy season shifts towards a later time in the future climate, water stress largely reduces and less grain-filling stress (for grain size, Fig. 6e) occurs. However the major impacts in the future climate become the heat stress during the flowering stage. The large increase in the maximum temperature (+2.8 °C) leads to a higher probability of heat stress during the sorghum's flowering period (Fig. 7), which causes a large decrease in the number of grains compared to the historical climate (Fig. 6d) and leads to yield loss. To summarize, heat stress in APSIM primarily happens during the flowering period to affect grain number formation, while grain size formation during the grainfilling period in APSIM is only influenced by water stress, and these two factors combined explain the negative impacts in the historical climate and for adaptation (Fig. 6f).

SARRA-H has the mechanism to simulate crop growth response to water stress but not to heat stress in the currently used version. Increasing thermal time similarly lengthens the growth cycle in SARRA-H, however due to the different phenology of post-flowering period simulated in SARRA-H compared with APSIM (see discussion in 3.2), SARRA-H does not show a large water stress impact for crop yield; instead, the increased growing season length enhances crop yield in the historical climate in SARRA-H. The negative adaptation impact in SARRA-H is primarily explained by the relative hastening of the growing season under future climate, i.e. for the same amount of thermal time increase, SARRA-H in historical climate has longer gain in growth length and higher yield than in the future climate, and thus the adaptation impact in SARRA-H is negative.

3.5. Sim 5: water harvesting

Both crop models show relatively small impacts from water harvesting in historical climate (APSIM: +1.5%; SARRA-H: +4.0% in mean yield for all stations) and for adaptation (both models have results not significantly different from zero). This finding is somewhat surprising given that some studies emphasized the potential importance of water harvesting (e.g. Rockström and Falkenmark, 2015). However, when corroborating our findings with the simulated hydrological variables from our models and observations, we conclude that water harvesting (if only from surface runoff) does have very limited impacts on crop yield in West Africa. Specifically, we find that the two crop models simulate similar amounts of runoff (mean annual runoff at the site level in mm/year: SARRA-H runoff = APSIM runoff*0.912 + 16.7, R^2 = 0.985, p-value < 10^{-5}, Fig. S2), and the magnitude of the simulated runoff is also consistent with the observation-based runoff estimation from Global Composite Runoff Fields, which is derived from station-level runoff measures from Global Runoff Data Base (GRDB) (Fekete et al., 2002) (Fig. S5). SARRA-H has slightly higher runoff ratios (0.074) than APSIM (0.055), meaning that over the whole study region less than 7.5% of the total rainfall is converted to runoff. Assuming farmers can harvest 50% of these runoff and use them for irrigation (we vary this efficiency by 30%, 50% and 70% and the results show little difference, Fig. S6), then crops get an extra amount of water that is equivalent of ∼3.8% of the total annual rainfall. Based on a prior study using the same crop models and crop cultivars in West Africa (Guan et al., 2015), the regional crop yield sensitivity is about 2% increase with 10% rainfall increases. Thus the expected crop yield benefits is less than 0.7%, which is in the same magnitude as our results; our results are slightly higher due to the fact that we apply the added irrigation when water stress starts to happen, and this slightly increases the use efficiency of irrigated water.

At the level of individual sites and GCMs, we find different patterns between APSIM and SARRA-H (Fig. 8). APSIM shows a general pattern of increased positive yield impact with rainfall amount, with a few cases having a negative yield impact in wet regions due to the nitrogen leaching caused by increased irrigation. The small yield response in the low rainfall regime (<800 mm yr^{-1}) in APSIM may be due to the reason that the very small amount of the irrigated water becomes soil evaporation before they can be used by crops; and only when the irrigated water amount is significantly large, the irrigation starts to show benefits for crop yield in APSIM. Instead, SARRA-H shows a general pattern of a decreased positive yield impact with rainfall amount, which is more as expected as the previous work (Guan et al., 2015). Though the two models simulated similar magnitudes of runoff for the whole study region, they nevertheless have differences in how they simulate the hydrological processes and can bring uncertainties to the results (Guan et al., 2015). A scrutiny of the hydrological processes may be beyond the scope of the current work. Given the difference between the two models, the general impact of water harvesting is relatively small (+1.5 to +4.0%) for different climate periods in both models.

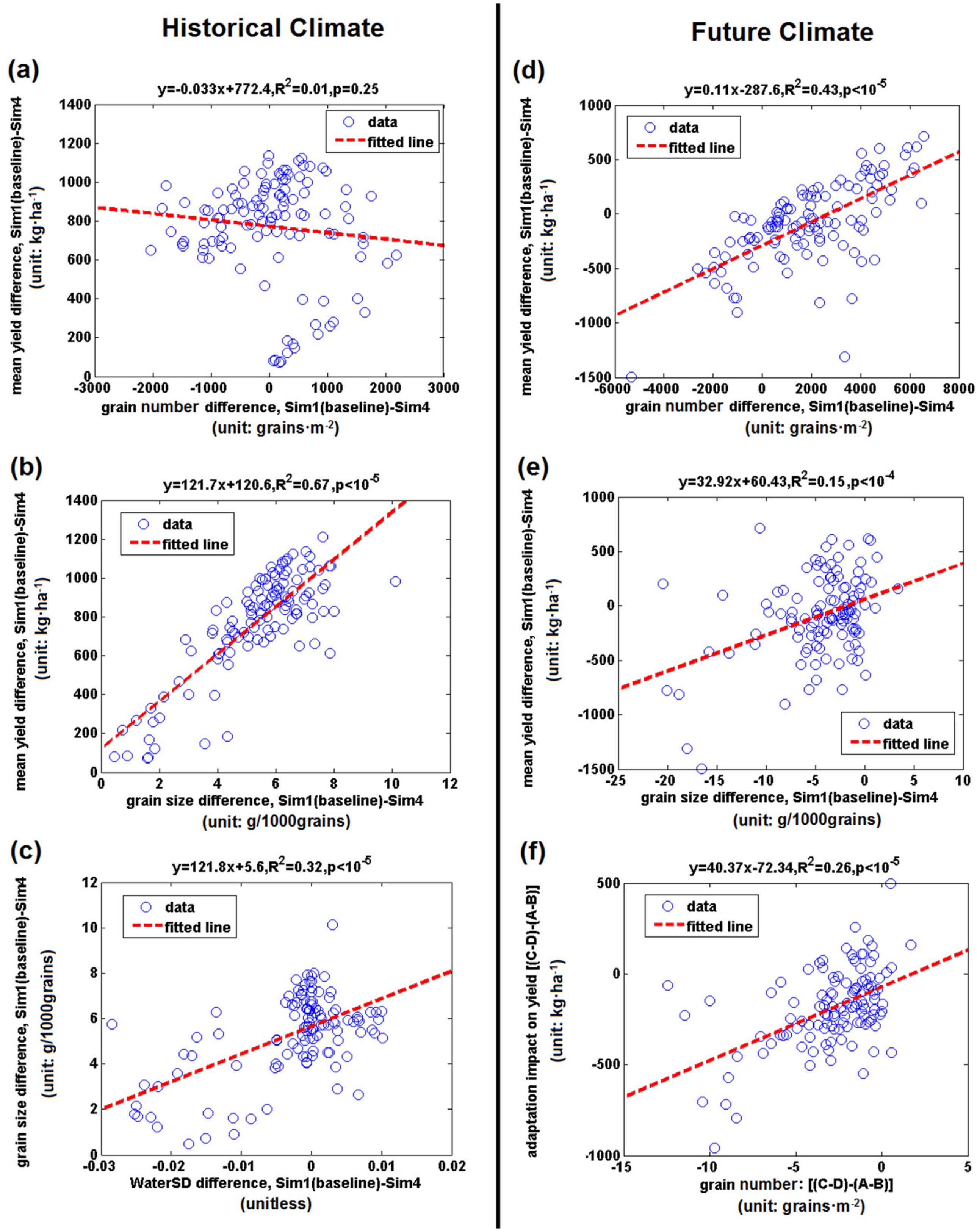

Fig. 6. Response of crop yield to grain number and grain size between the Sim 4 ("Thermal time increase") and Sim 1 (baseline) in the historical and future climate for APSIM simulations (panel a,b,d,e). Panel c shows that water stress can largely explain the grain size changes in the historical climate, where "WaterSD" is an indicator of water stress that bounds between 0 and 1, and a lower "WaterSD" means a higher water stress. Panel f shows the adaptation impact of Sim 4 is largely driven by the changes in grain number induced by higher temperature during the flowering stage in the future climate.

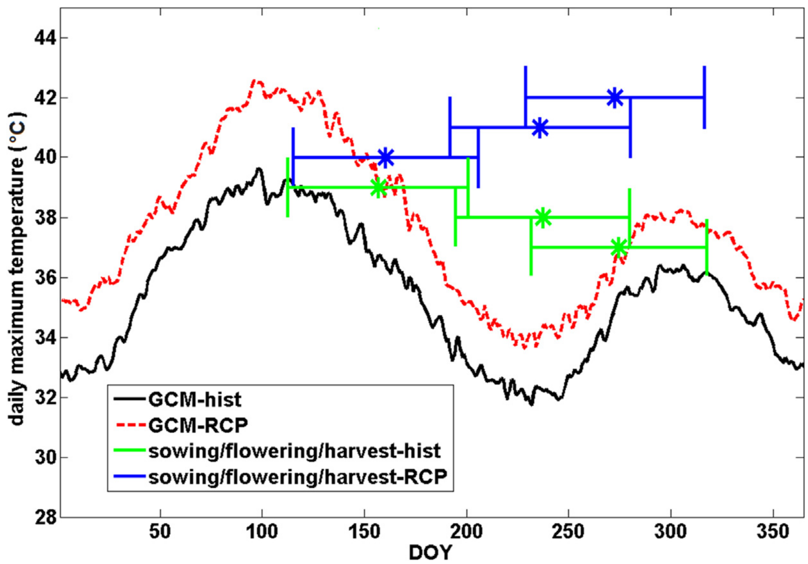

Fig. 7. Average maximum temperature of the historical and future RCP8.5 period for the study area, and the critical phenological periods (sowing, flowering, and harvest) simulated in APSIM for the historical and RCP8.5 period. The "flowering" stage refers to the period from "floral initiation" to the "appearance of the flag leaf".

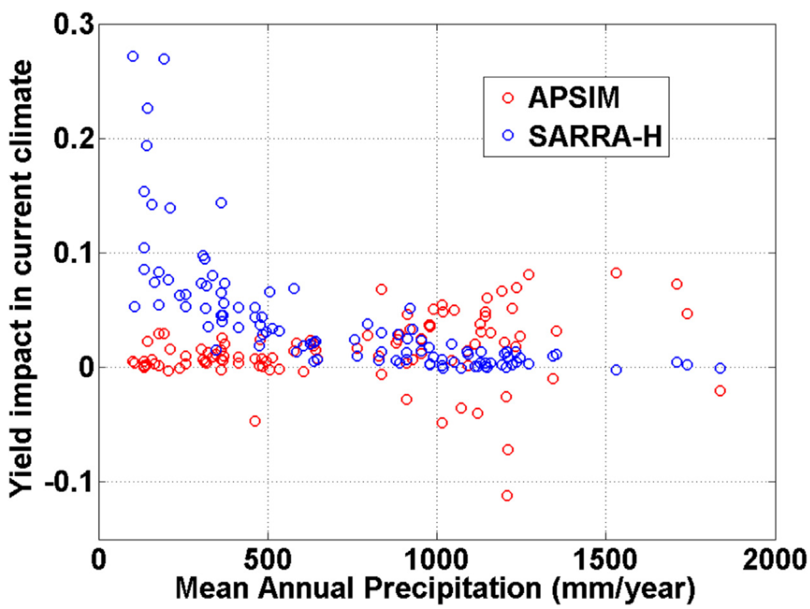

Fig. 8. Yield impact in the historical climate for "Water harvesting" (Sim 5) as a function of mean annual precipitation in the historical climate. All the sites (13) and GCMs (8) are shown for both crop models (APSIM: red, SARRA-H: blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

3.6. Sim 6: increased temperature resilience of grain number formation (only for APSIM)

Since only APSIM has the mechanism to simulate heat stress during the flowering period to affect grain number formation, it has the ability to simulate the impact of increased resilience to heat stress. We find that this proposed adaptation option has little benefit in the historical climate, because the maximum temperature during the critical period of flowering is mostly lower than 36 °C (Fig. 7), which is the temperature threshold that triggers heat stress on grain number formation in APSIM. However, this option shows significantly positive impacts of adaptation (+4.5%), because the increased maximum temperature projected in the future has surpassed the 36 °C threshold during the flowering period. The "graintempfactor" simulated in APSIM, which indicates the heat stress level for the grain number formation, can largely explain the changes in the formed grain number ($R^2 = 0.80$, Fig. S7a), which further explains the changes in the final crop yield (Fig. S7b). Our findings that grain sensitivity to heat is relatively unimportant in current climate, but much more so in future climate, are both in agreement with the simulations of Singh et al. (2014) for sorghum in two sites in Mali.

3.7. Assessing the changes in yield variability for different proposed adaptation options

So far we have primarily focused on assessing the different proposed adaptation options in terms of their change in mean yield. Next, we will assess three aspects related to the yield variability and risks (Fig. 9). The three aspects are complementary to each other:

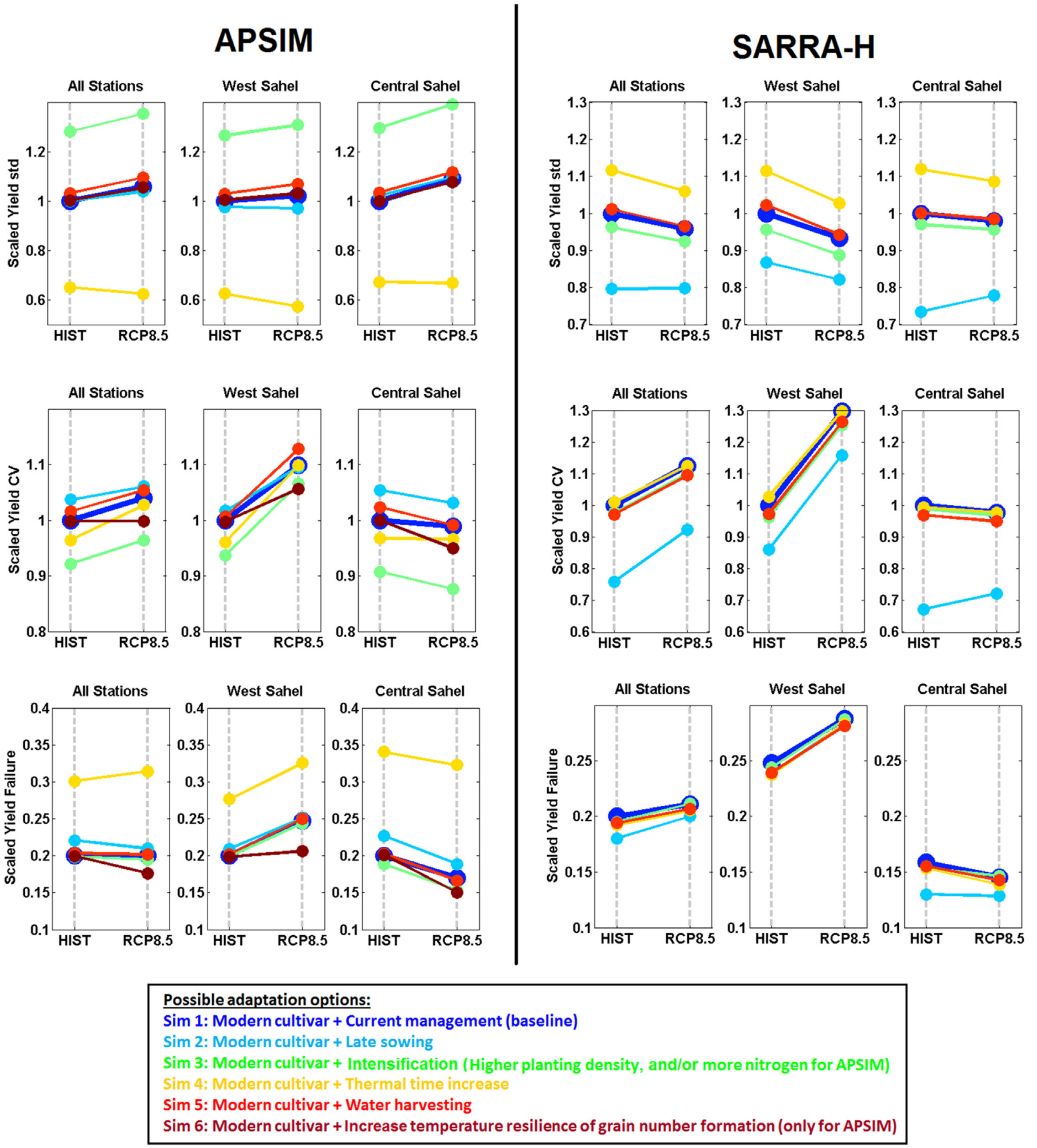

Fig. 9. Similar to Fig. 3, but for simulated changes in yield variability, i.e. standard deviation (std) (first row), coefficient of variation (CV) (second row), and yield failure rate (third row), averaged over all the 13 sites and all the 8 GCMs. The std and CV values have been scaled by the Sim 1 (baseline).

standard deviation (std) characterizes the absolute inter-annual variability in yields, the coefficient of variation (CV) assesses the relative inter-annual variability of yield as it has been normalized by the mean yield, and yield failure rate specifically assesses the changes of crop yields below a critical threshold (here 20th quantile of historical yield in the baseline simulation, Sim1), i.e. the change in the left tail of the yield distribution.

We find that std shows a similar trend as the mean yield change (Fig. 3), which suggests variability generally scales with mean yield changes. However, "Late sowing" (Sim 2) and "High planting density" (Sim 3) in SARRA-H have lower std than the baseline (Sim1), which is different from the pattern of the mean yield change (Fig. 3).

CV and yield failure rate show a similar regional pattern as mean yields, with West Sahel having an increased risk of yield variability in the future climate compared with the historical climate, and Central Sahel having a decreased risk of yield variability in the future. Focusing on specific adaptation options, we find that the CV of "Intensification" (Sim 3) in APSIM is smaller than the baseline (Sim 1), and the CV pattern is also reversed from the std pattern. The yield failure rate of "Intensification" (Sim 3) in APSIM does not

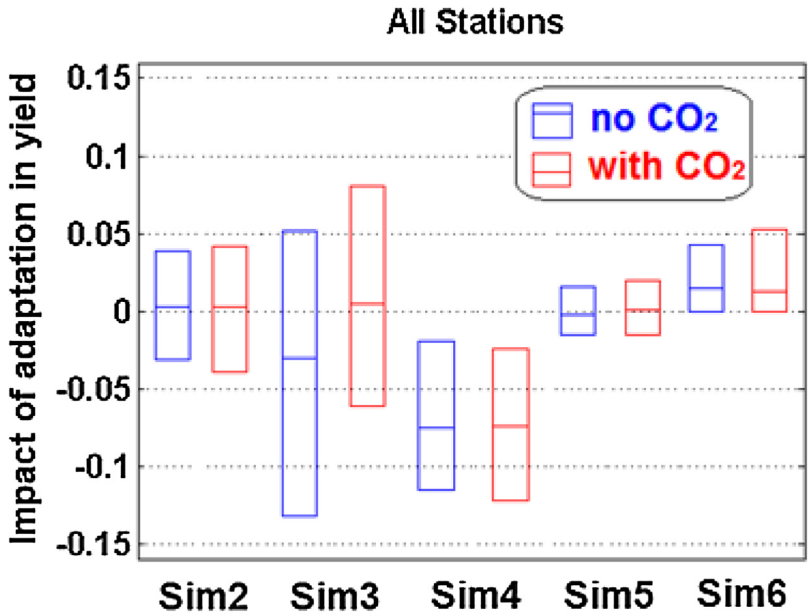

Fig. 10. APSIM simulated impact of adaptation with and without CO_2 fertilization effects for all the station-aggregated results. The boxplots show the 25th, median and 75th percentile yield responses across 8 GCMs. Sim2-Late sowing; Sim3-Intensification; Sim4-Thermal time increase; Sim5-Water harvesting; Sim6: Grain number sensitivity to temperature.

have a significant change from the baseline (Sim 1) for West Sahel, but is smaller than the baseline (Sim 1) for Central Sahel. We also find that "Thermal time increase" (Sim 4) in APSIM has a larger yield failure rate than other simulations, though its change between the historical and future climate is similar as other simulations. "Temperature resilience of grain number formation" (Sim 6) in APSIM did not have much effect on variability in the historical climate, but it has an obvious reduction in yield variability (CV: −5.2% relative to the CV of the baseline historical simulation; yield failure: −3.0% for the baseline yield quantile) in the future climate. The reason is similar as before that the critical temperature threshold related to the grain number formation was seldom exceeded in the historical climate but is frequently passed in the future climate. "Late sowing" (Sim 2) in APSIM has an increased risk of yield variability (for both CV and yield failure), but it has a reduced risk of yield variability in SARRA-H. We find that the yield variability change of water harvesting mostly follows the mean yield change; in other words, in our simulation water harvesting does not reduce the risks of yield variability.

4. Discussion

4.1. Uncertainties from crop model differences

The simulated results of the two crop models here (i.e. the changes in mean yield and yield variability) have confirmed our previous study (Sultan et al., 2014) about the regionally distinctive responses under climate change for West and Central Sahel. This consistency primarily arises from the similar responses to water stress in the two models, and to a certain extent from their responses to temperature increases (i.e. higher temperature hastens the growing cycle). However, the two models also show some obvious differences in assessing various proposed adaptation options. We find that the uncertainties arising from different crop models in many cases are larger than those from the ensemble climate model projections, consistent with the prior finding (Rosenzweig et al., 2014). Again, it is worth noting first that the recent SARRA-H model has incorporated advanced functionality (including improved nitrogen fertility modeling and CO_2 fertilization effect), thus the following discussion only applies to the comparison between APSIM v7.5 and SARRA-H v3.2, as these two models were the latest version when we started this research. The following five aspects are the major features that drive the differences in the simulated responses between the two crop models (APSIM v7.5 and SARRA-H v3.2).

1) Nitrogen cycle. Though SARRA-H has implicitly incorporated some nitrogen impacts in its parameterization (based on calibration of the field data in West Africa) (Sultan et al., 2013), it does not explicitly simulate the nitrogen cycle as APSIM. In the "Intensification" (Sim 3), when using only higher planting density both models show similar results (i.e. little difference from the baseline), but the explicit nitrogen cycle allows APSIM to simulate the combined effects of higher density and higher fertilizer inputs, which shows a large yield increase from the baseline.
2) Heat stress. "Heat stress" by convention refers to the temperature-induced stress during the flowering and grain-filling periods for a crop (Lobell and Gourdji, 2012). APSIM has an explicit parameterization to simulate the heat stress impact during the grain formation period, which allows the assessment of the proposed adaptation "Temperature resilience of grain number formation" (Sim 6).
3) Effect of CO_2 fertilization. Since only APSIM has incorporated the parameterization of CO_2 fertilization, here we investigate APSIM's performance with and without this effect for all the simulations (Fig. 10). The CO_2 fertilization in APSIM is achieved only through linearly increasing the transpiration efficiency by 37% at 700 ppm compared with at 350 ppm (Harrison et al., 2014), with no other direct effects. Fig. 10 shows that only Intensification (Sim 3) in APSIM has a pronounced adaptation impact on yield at a higher CO_2 environment (+4.2% in yield median). This is consistent with our expectation, as CO_2 fertilization should have little connection with other adaptation options. However, with ample nitrogen inputs (i.e. Sim3, Intensification), crops should be able to better take the advantage of environmental benefits (such as

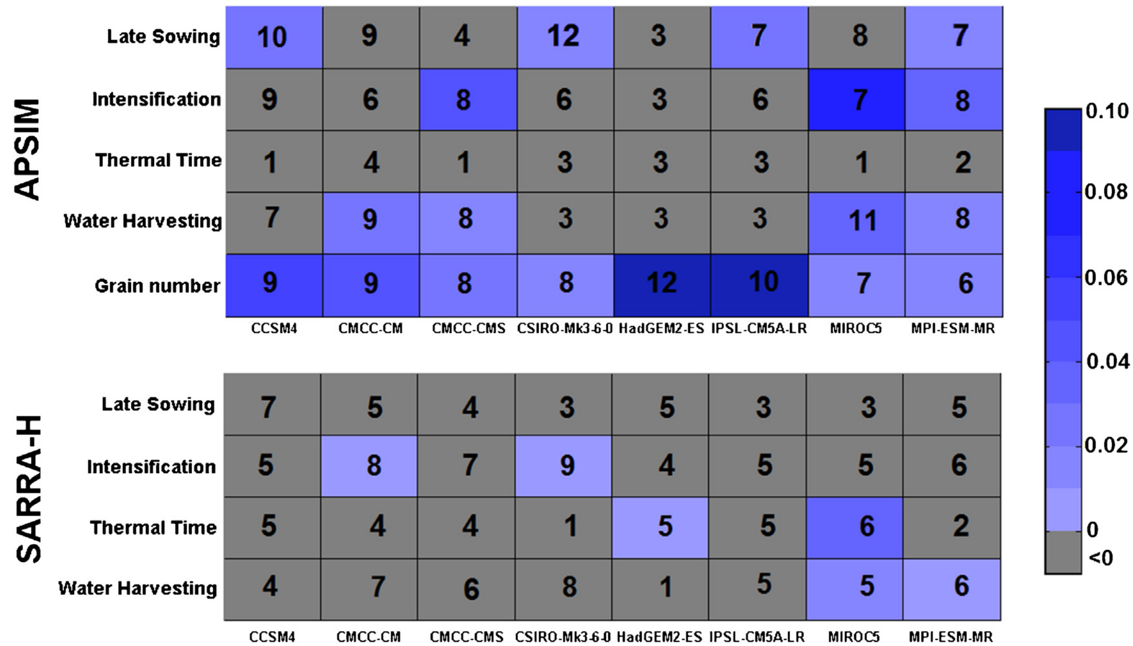

Fig. 11. Impact of adaptation ([(C–D) – (A–B)]/B) for different proposed adaptation options aggregated for different GCMs (all scaled by the baseline historical mean yield). Positive impacts are shown in blue, and negative impacts are all shown in gray. The number inside each box indicates the number of sites that have positive impact of adaptation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

increased rainfall or increased water use efficiency through CO_2 fertilization) (Sultan et al., 2014).

4) Crop phenology. Both models follow similar thermal time accumulation mechanisms to model phenology, with slightly different mechanisms to model phenological sensitivity to photoperiod (Sultan et al., 2014). It is primarily the calibration of the phenology scheme (in the current climate) that led to a nearly reversed response in “Late sowing” (Sim 2) between the two models, though the absolute impact is very small (Figs. 3 and 4). Both models were only calibrated from sowing to the flowering period, leaving the post-flowering period less reliable. This variation between the two models lead to different water stress responses. This result also highlight the importance of simulating a correct phenology for the crop adaptation study.
5) Hydrological process. Though the overall effects of Water harvesting (Sim5) for the whole region is similarly small for both models, they show quite different patterns at the site level. The simulated runoff difference between the two models may explain the yield difference. The difference in parameterizations of the hydrological processes in these two models have been discussed before (Guan et al., 2015). In order to reduce uncertainties, we need to collect comprehensive observational data and apply multi-model inter-comparison to determine which parameterization most faithfully reproduces the observations. This is especially critical for rainfed agriculture regions in dry/semi-dry climate, such as West Africa.

In sum, our findings demonstrate that different parameterizations of physical and biological processes in crop models play a critical role in assessing different proposed adaptation options. Our results echo with the arguments by others of the need to improve certain processes in crop models and to more systematically understand the model requirements for simulating yield responses to future climate change and adaptations (Craufurd et al., 2013; White et al., 2011).

4.2. Uncertainties from climate model differences

The boxes in Fig. 4 show the uncertainties in our simulated results arising from the use of different climate model projections. Here we further unpack these uncertainties by looking at the individual GCM's results for the simulated adaptation impact (Fig. 11, Figs. S10–S12). We find that our bias-corrected climate forcing from different GCMs still have some divergence in the absolute magnitudes of rainfall (less so in temperature) when benchmarked with the historical climate observations (Fig. S10), though the effect of the simulated changes in temperature or rainfall between the historical climate and the future climate seems more convergent across different GCMs (Figs. S11 & S12).

Given these differences in GCMs, we find that all the GCMs simulate a positive impact of adaptation for “Temperature resilience of grain number formation” (Sim 6) in APSIM (Fig. 11), and this impact of adaptation in general becomes larger at warmer climate projection scenarios (Fig. S12), consistent with our expectation that heat-tolerant varieties should be more favored in higher temperatures. Meanwhile, all GCMs lead to a negative impact of adaptation for “Thermal time increase” (Sim 4) in APSIM and for “Late sowing” (Sim 2) in SARRA-H. The GCMs that show a positive impact of adaptation for “Intensification” (Sim 3) in APSIM are primarily those with a significant increase in rainfall (Fig. S11), consistent with our previous interpretation in Fig. 5. Overall, MPI-ESM-Mr shows the most positive impacts of adaptation for APSIM (4 out of 5), and MIROC5 shows the most positive impacts of adaptation for SARRA-H (2 out of 4).

Our results show that differences in the accuracy of GCM simulations of the current climatology (e.g. for rainfall, see Fig. 5 and Fig. S11) play an important role, comparable to the role of differences in projections, in determining the sign and magnitude of the impact of adaptations, especially for those proposed adaptation options that are highly sensitive to temperature (e.g. “Thermal time increase” and “Temperature resilience of grain number formation”) or to rainfall (e.g. “Intensification”). The statistical correction of temperature biases is much more straightforward than that of rainfall biases, and thus the most urgent task is to improve mean rainfall accumulation and sub-seasonal rainfall characteristics (frequency, intensity, rainy season length) in climate models. The challenge to improve the simulation of these rainfall features may not be fully addressed in the near term in the GCMs, as it requires formidable computational capacity to resolve the convective processes. Finally, it is worth noting that we did not consider the uncertainties in the bias correction/downscaling technique here, though we fully acknowledge that these uncertainties can be significant (Glotter et al., 2014; Hawkins et al., 2013).

4.3. Robust adaptation options for crop production for West Africa

Our results reveal that among all the proposed five adaptation options, only "Temperature resilience of grain number formation" (only in APSIM) shows a robust positive impact of adaptation across sites and GCMs. This option also robustly shows a reduction of the relative yield variability (i.e. CV) and yield failure in the future climate. In scenarios of projected rainfall increases in the Central Sahel, "Intensification" is also a true adaptation. However, "Intensification" appears not to significantly reduce the yield failure rate. Beyond the above two options, all other three options do not qualify as true adaptations, i.e. they are not able to mitigate the impact of climate change.

5. Conclusions

With more available funding designated for climate change adaptation (e.g. Green Climate Fund), scientific studies for assessing various adaptation options and prioritizing investments of limited adaptation funds are urgently needed. Here we have conducted a case study in West Africa to comprehensively assess five possible adaptation options for the sorghum production system under climate change (2061–2090, RCP8.5 scenario). We have developed a new assessment framework to account for both the impact in current climate and the true adaptation benefit (i.e. reduction of climate change impacts); and we have also simultaneously considered the changes in the mean yield and in the inter-annual yield variability. We have discovered that only the option "Temperature resilience of grain number formation" is qualified as a true climate adaptation for the whole region (+4.5% in yield), and "Intensification" (combining both higher planting density and higher fertilizer rate) can be an adaptation in Central Sahel (+4.8% in yield by APSIM). The other three proposed options do not qualify as true adaptations.

We also find that though "Temperature resilience of grain number formation" can benefit in the future climate, it offers little benefit for the historical climate as the temperature in the historical period (1961–1990) during the relevant flowering stage was lower than the critical temperature threshold. "Intensification" with higher fertilizer inputs can dramatically improve the mean yield by +50% in the historical climate, though it may not help reduce the yield failure rate. "Intensification" with higher planting density alone does not help much in the historical climate. Using surface runoff-based "water harvesting" with a relatively simple irrigation scheme implemented in our study has shown little impact in both historical and future climate, primarily due to the small amount of water that can be harvested. It is worth noting that "water harvesting" should not be confused with irrigation using pumped ground water or channel streamflow; the latter may generate much larger positive impacts for yield, though the economic cost for building relevant infrastructures will also be very high and may not be adopted by farmers for low-value crops such as sorghum. "Late sowing" and "Thermal time increase" show inconsistent patterns between the two crop models, due to various reasons; though their absolute impact are very small (<4%) regardless of their signs.

Though the two crop models simulate a generally consistent pattern of yield change at the regional scales between the historical and future climate (in terms of mean yield and yield variability, Figs. 3 and 9), they show differences in their adaptation impacts. These differences are primarily caused by the different parameterizations of nitrogen cycle, heat stress, CO_2 fertilization, crop phenology calibration and hydrological processes. We find that the uncertainties arisen from the two crop models are in general larger than those coming from the ensemble climate projections from different GCMs. Future efforts to reduce uncertainties of crop modeling should be devoted to compare different parameterizations of an individual hydrological or biophysical process, and decide the optimal parameterization through corroborating with measurements (Jin et al., 2016). From the climate forcing perspective, we find that both the absolute magnitude of the simulated climatology and the simulated changes between the historical and the future climate play important roles in determining the signs of the proposed adaptation options; the above information may help climate modeling community further focus their effort in improving climate projections and reducing their uncertainty.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agrformet.2016.07.021.

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