Which is more important to sorghum production systems in the Sudano-Sahelian zone of West Africa: climate change or improved management practices?

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Abstract

The productivity of smallholder farming systems is held back by poor soil fertility, low input levels and erratic rainfall distribution in the sorghum-based cropping systems of the Sudano-Sahelian zone of West Africa. We assessed the sensitivity of current agricultural practices to climate change and to improved management practices: (i) increased fertilizer application combined with increased plant populations and (ii) use of improved sorghum varieties. We applied the Decision Support Systems for Agro-Technological Transfer (DSSAT) Cropping Systems Model, and the Agricultural Production Systems sIMulator (APSIM), for a multiple-farm assessment (i.e. diverse types of management and soils) in Koutiala (Mali) and Navrongo (Ghana), which are representative sites for West African sorghum production systems. Baseline climate data from observed weather (1980-2009) and future climates from five Global Circulation Models (GCMs: 2040-2069) in two Representative Concentration Pathways (RCP 4.5 and 8.5) were used as inputs for crop models. In Navrongo, under current management, sorghum yields either decreased or increased compared to the baseline, depending on the crop models and the GCMs; changes in management options induced a yield increase of up to 256%. The addition of genetic improvement resulted in further yield increases (24%). In Koutiala, sorghum yield changes for future climates ranged from -38 to +8% assuming current management. Shifting to an improved cultivar had a marginal effect on grain yields, while increased fertilizer rates resulted in grain yield increases ranging of 20% and 153% for DSSAT and APSIM, respectively, assuming the current climate. We conclude that in the Sudano-Sahelian zone of West Africa sorghum, as it is cultivated today, appears moderately vulnerable to climate change, while doubling fertilizer inputs with an adjusted planting density, in the current climate, would more than double yields. However, by exploring farm diversity we established that, under certain conditions, the effect of the future climate might be as important as the effect of management changes in the current climate, hinting at the importance of locally-relevant management practices.

Keywords: crop modeling, soil fertility, temperature, heterogeneity, agriculture, management, climate change

Introduction

Improved crop productivity is required in the current and future production systems of West Africa. In a changing environment, genetic and agronomic interventions are being developed to cope with the effect of climate change and the need for sustainable intensification. Challinor et al. (2014) summarized more than 1700 simulations evaluating the effect of climate change on crop yields and stated that adaptation at crop level (improved cultivars or management practices) would help to increase yield by an average of 7 to 15% for three major crops: wheat, rice and maize. In West Africa, Faye et al. (2018) showed that cereal yields would decrease by between 2 and 5% with a temperature increase of 1.5°C and 2°C, respectively. Sultan et al. (2013) indicated that crop yields would be impacted by up to -41%, due mainly to temperature changes. In Mali, Traore et al. (2017) assessed the effect of climate change on maize and pearl millet yields. They indicated a maize grain yield loss caused by climate change of up to 57%, which could be offset by applying recommended fertilizer doses. Similar conclusions were drawn for pearl millet, but with a lesser effect of climate change (-10% grain yields) on this drought-resilient crop. Likewise, Rurinda et al. (2015) demonstrated the importance of management practices to offset climate change effects on maize yields in southern Africa.

Crop management is a key determinant for counterbalancing crop yield variability in low input farming systems (Tittonell and Giller, 2013). Sowing dates are important management decisions that can greatly influence crop yields (Guan et al., 2017) and yield simulations (Srivastava et al., 2016), particularly in the West African region, due to the high inter-annual variability of the onset of rains, with farmers' sowing decisions influenced by both climatic and socio-economic factors (Mertz et al., 2011). However, in most climate change assessment studies it is not often clearly discussed whether we should be focusing more on adaptation strategies, because of the potential effect of climate change on crop yields, or whether we should first address the issue of improving crop yield through appropriate management practices in the current production systems (Lobell, 2014). Indeed, the ability of these management practices to cope with the effects of climate change (i.e. adaptation strategies) has often been assessed in the literature (Parkes et al., 2018; Sultan et al., 2013) and is undeniable. However, few studies have compared the effects of future climates on the current production system with the effects of improved management practices on the current production system (Lobell 2014 and Guan et al. 2017). Lobell (2014) and Guan et al (2017) both addressed the importance of distinguishing the impact of management practices in the current climate and their impact in a future climate. It is important to consider such a distinction, in order to define management practices that can first increase productivity, but also practices that can increase the resilience of the systems to climate change.

Agriculture in the Sudano-Sahelian regions of West Africa is dominated by millet, sorghum, peanut and cowpea grown in annual rotation, or intercropped. Maize is also grown, but to a lesser extent. Very few farmers apply mineral fertilizers due to limited access to credit and agro-inputs, or an outright lack thereof. As a result, average yields of cereals and legumes are low. As mentioned by Lobell (2014), one of the biggest challenges to achieving food security in Africa remains management of poor soil fertility. Further, compared to maize, sorghum has been less modeled despite its higher drought tolerance and its importance as a staple for semi-arid dwellers. A few exceptions can be found in the literature, but usually the studies (Sultan et al., 2014, Guan et al. 2017, Faye et al. 2018,) were carried out on a regional scale rather than on a local scale. One exception can be mentioned: Singh et al. (2014) showed that, under climate change, heat tolerance traits would contribute to yield gain increases at Cinzana (up to 9%) and Samanko (up to 7%). However, that study only considered one GCM (General Circulation Model) and cultivar adaptation options, and did not model the effect of altered agronomic management strategies, such as fertilizer rates, planting density and planting windows, which are important management practices for optimizing yields in the current sorghum production systems of the Sudano-Sahelian zone of West Africa.

In most global or regional modeling studies, adaptation strategies are applied as a blanket recommendation regardless of context, while some management practices might have more potential in one location than in another (Descheemaeker et al., 2019). Hence, even though the literature has clearly demonstrated that climate change affects sorghum crop yields and the potential of management practices to improve crop yields in the current West African farming systems (Sultan et al., 2014), the focus has rarely been on a local scale to assess locally-relevant management strategies. In this study, we assessed the potential of these strategies to improve sorghum production and assessed their variability across time and space using multiple farms (i.e. diverse levels of management and soils), comparing their effect with the effect of climate changes under the same current production systems.

The main objectives of this research were to: (i) assess the effect of future climates on sorghum grain yields under current production systems in the Sudano-Sahelian regions of West Africa, (ii) assess the effect of improved management practices on sorghum grain yields, (iii) compare the effect of future climates and improved management strategies on sorghum grain yields in the current production systems, in order to guide the choice of locally-relevant options and help to direct policy-makers in prioritizing their action, and (iv) assess the level of agreement between the 2 most frequently used models in this area of study (i.e. uncertainty, which it is important to consider to guide policy makers in their recommendations).

Materials and methods

Study sites

Our research focused on two study sites that were representative of the Sudano-Sahelian zone of West Africa, where sorghum is one of the main staple crops. Navrongo (Upper East Region, Ghana) lies at 10.89°N and 1.09°W at an elevation of 198 m. Koutiala (Mali) is at 12.37° N and 5.47° W, at an elevation of 350 m. Agriculture remains the dominant economic activity at both sites and predominantly involves smallholders. The main difference between the two sites is the level of farming system intensification. Koutiala, being part of the cotton belt in Mali, benefits from better access to fertilizers, inducing a relatively better soil fertility status compared to the soils in Navrongo.

Navrongo features a unimodal rainfall pattern (annual mean total: 969 mm) beginning in May and ending in September/October. The minimum and maximum daily mean temperatures over this period are 19.2°C and 40.4°C respectively. The amount of annual rainfall is marked by high inter-annual and intra-annual variability that influences vegetative production and has a negative effect on crop production. In Koutiala, the cotton zone of southern Mali, rainfall starts in May and ends in October, with an average annual rainfall of 935 mm, a moderate drought risk (20% inter-annual variability), with a mean daily temperature varying between 13.8°C and 36.6°C. Detailed meteorological records have been compiled by AGRHYMET Regional Center and National Meteorological Agencies.

Crop models

Two crop models were used for this *ex-ante* assessment study: (1) the Decision Support System for Agro-technology Transfer (DSSAT v. 4.6) Cropping Systems Model (Jones et al., 2003), and (2) the Agricultural Production Systems Simulator (APSIM v. 7.5) (Holzworth et al. 2014). The DSSAT model was previously used in simulation studies in Ghana and Mali (Akinseye et al., 2017; MacCarthy et al., 2010), and in the Sahel (Traoré et al., 2007). This version of the APSIM model was also calibrated and used in previous studies in West Africa (Akinseye et al., 2017; MacCarthy et al., 2009). For the model simulation set-up, we followed the Agricultural Model Intercomparison and Improvement Project (AgMIP) Regional Integrated Assessment (RIA) approach (Rosenzweig et al., 2013). Field information on crop yields was collected from a household survey at both sites, and we assessed the effect of future climates and of improved management practices on sorghum grain yields.

Reference data

The reference survey data used for Navrongo were collected in 2012 on 276 smallholder farms, 169 of which cultivated sorghum. The survey data included observed yields, cost of manure and fertilizer applications, household size and geo-reference, and the sowing window. Within each planting window defined in the survey (from mid-May to mid-July), a sowing rule was then applied to automatically trigger planting after 25 mm of accumulated rainfall in 2 rainfall events (Figure 1a). Neither manure nor fertilizer were applied on sorghum (information derived from the cost of manure and fertilizer applications). The observed sorghum yields ranged from 33 to 1090 kg ha^{-1} with a low average yield of 388 kg ha^{-1} (Figure 1b).

FIGURE 1

In the Koutiala district, we retrieved sorghum yields ranging from 90 to 1942 kg ha^{-1} (Figure 1b) from the RuralStruc World Bank survey undertaken in 2007. The average sorghum yields at this site were 733 kg ha^{-1}. Data were obtained from 153 households in six villages, namely Namapala, Try, Tonon, Signe (Sirakele), Gouantiesso and Kaniko, and included information about harvested yields and the total N applied (at farm level). The survey data did not include information about sowing dates or soil types for each household. As such information is essential for setting up crop models, we used expert-based rules to represent the diversity of farms and the heterogeneity typical of the low input farming systems of the Koutiala district. Sowing dates were randomized based on expert knowledge about farmer practices, where farmers planted cotton by 10 June, on average, followed by maize 7 days later and sorghum 15 days after the cotton. Figure 1a shows the frequency of sowing dates for sorghum at both sites.

For both sites, the soil data used for the study (Table 1) were those reported in the literature, supplemented with soil survey data. To assign a soil to each household, we allocated the soils according to the village location and farm location (i.e. identification of soils present in the village from a soil map produced by PIRT, 1983), and sorghum yield levels (i.e. better soil where sorghum yield was high). The models were initialized 30 days prior to the sowing window,to account for initial water conditions, which were not available in the survey data. This initialization period was sufficient in the study area context, as the planting date occurred at the beginning of the rainy season after a dry season of around 8 months. The initial N in the soils varied from 9 to 20 kg. ha^{-1}, values similar to those found in the region (Traore et al. 2017).

TABLE 1

For Navrongo, the sorghum variety used was *ICSVIII* (calibration and validation: MacCarthy et al., 2009, and MacCarthy et al., 2010). *ICSVIII* is an improved cultivar being promoted by agricultural research in the northern part of Ghana. *ICSVIII* is not photoperiod-sensitive. In Koutiala, the locally common sorghum variety *CSM335* (calibration and validation: Akinseye et al., 2017) was assumed to be cropped by all the farmers. *CSM335* is a long cycle cultivar taking up to 130 days to mature and is moderately photoperiod-sensitive. Table 2 shows the genetic coefficients and their values as used in the study.

TABLE 2

Management levels

To test the effect of management practices on the current production systems, two management packages were simulated that included improved agronomy over the baseline practice, with and without improved genetics.

Improved agronomy involved the addition of 30 kg N ha^{-1} over the baseline fertilization rate, combined with an increase in the plant population from 4 to 5.5 plants m^{-2}. These changes in management practices were chosen after carrying out a sensitivity analysis (i.e. yield reaching a plateau) and taking into consideration the local context (i.e. affordability of and access to inputs). In Navrongo, we first improved the management practices (as it was a very low input system) and then we combined this intervention with the inclusion of an improved cultivar. In Koutiala, the first intervention package involved genetic improvements on the cultivar over the baseline cultivar, whilst the second intervention package was a combination of management and genetic modifications. This choice was made because of the differences in the current agricultural systems, with Koutiala having slightly more intensive farming systems, using fertilizer inputs in the main crop of cotton and maize. In Navrongo, much less fertilizer was used, hence we considered that adding fertilizer and improving management practices should be the first intervention put in place.

Genetic improvement was intended to create a cultivar that was heat stress-tolerant and had a higher grain yield potential. To that end, we altered the phenology and partitioning to simulate plants with shorter stems (shorter vegetative phase) to lessen the susceptibility to wind, and a higher reproductive mass ratio (longer reproductive phase, and higher grain weight) to improve the harvest index (Singh et al. 2014). Hence, we shortened the time from emergence to the end of the juvenile phase by 10 and 20% (for *CSM 335* and *ICVS III,* respectively) and lengthened the photo thermal time from flowering to maturity by 10 and 20% (for *CSM 335* and *ICVS III,* respectively), and we increased the relative partitioning of assimilates to the panicle (G2 in DSSAT and dm_per_seed in APSIM) by 20% (Table 2). Additionally, the upper optimum temperature threshold of RGFILL (i.e. relative grain filling rate) was increased (from 35 to 37°C) for *CSM 335* to lengthen the optimum period when grain filling occurred, thereby making it more tolerant of heat stress.

Current and future climate data

Baseline (1980-2009) and future (2040-2069) climates from 5 Global Circulation Models (GCMs) for each of the Representative Concentration Pathways (RCP), 4.5 and 8.5, were used as inputs for the crop models, following the Agriculture Models Inter-comparison and improvement Project (AgMIP) protocol (Rosenzweig et al. 2013, Ruane et al. 2015). The choice of using multiple climate scenarios is a way of considering climatic uncertainty related to these climate models (Corbeels et al. 2018). The historical data used in this study consisted mainly of daily observations of rainfall, solar radiation and temperatures available at the AGRHYMET Regional Center for the 1980-2010 period. When needed, missing data were replaced with corresponding AgMERRA time series data (Ruane et al., 2015), with bias adjustment according to a comparison between AgMERRA and the monthly climatology of the observed station.

FIGURE 2

For future climates, 5 GCMs were selected for each site from a total of 29 GCMs that best described the climate of each site following a quadrant approach (Ruane and McDermid, 2017), geared to sampling 5 climate scenarios relevant to the region, and to representing the diverse possible climate scenarios (even if not equally probable). In this approach, a scatterplot combining the changes in temperature and precipitation (taking into consideration the number of rainy days), compared to the baseline, was plotted (Figure 2) to determine whether the GCM outputs leant towards relatively warmer and drier, warmer and wetter, cooler and wetter, cooler and drier, or average conditions for two Representative Concentration Pathways (RCP), 4.5 and 8.5. Hence, out of the 29 GCMs those best representing Hot/Wet, Hot/Dry, Middle, Cool/Wet and Cool/Dry future climate scenarios were identified to generate daily weather data for the 2 study sites (Figure 2). Table 3 provides the list of GCMs selected for Navrongo (Ghana) and Koutiala (Mali). All the selected GCMs simulated a significant increase in monthly temperatures at both sites, but the changes were not uniform across GCMs and sites. Overall, in the RCP 8.5 scenario temperatures were expected to increase by up to 2.72°C and 3.10°C in Navrongo and Koutiala, respectively. For precipitation, the expected changes were more contrasting, with a 6% decrease in the driest scenario and a 15% increase in the wettest in Koutiala (resp. Navrongo: -3% and +12%).

TABLE3

Scenario analysis

Baseline simulations (current climate and farmer practices) were used to validate input parameters and assess the ability of the models to reproduce the observed yield variability in the survey data (i.e. capturing farm diversity). Outputs from these simulations were used to assess yield variability due to management practices (across households) and due to climate (across years). To assess these variabilities, we computed the coefficients of variation across farms for all years (Vm) and across years for all farms (Vw), as follows:

$$Vm = \left(\sqrt{\frac{1}{hh}\sum_{i=1}^{y}\left(x_{hh_i} - \overline{x_{hh}}\right)^2}\right) \Big/ \bar{x} \qquad \text{Equation 1}$$

$$Vw = \left(\sqrt{\frac{1}{y}\sum_{i=1}^{hh}\left(x_{y_i} - \overline{x_{y}}\right)^2}\right) \Big/ \bar{x} \qquad \text{Equation 2}$$

Where hh and y are the number of households and year respectively, x_{hh_i} is the average sorghum grain yield for each household, x_{y_i} is the average sorghum grain yield for each year ,and $\bar{x}$ is the average grain yield across years and households.

For the *ex-ante* assessment study, the two crop models were run for each combination of eleven future climates (baseline and ten future climates) and three management scenarios (current management practices and the two intervention packages) to assess the sensitivity of current sorghum production systems to future climates and (separately) improved management practices. First, we set out to assess the sensitivity of the current agricultural production systems to future climates (i.e. the production system remained in its current state). Second, we assessed the effect of the intervention packages in the current systems. For both questions, we calculated the average percentage change relative to the baseline yield.

$$Change\ in\ value\ (\%) = 100 * \left(\frac{Scenario\ sorghum\ yield - Baseline\ sorghum\ yield}{Baseline\ sorghum\ yield}\right) \qquad \text{Equation 3}$$

Further, to understand differences between the two crop models under future climates, we conducted a sensitivity analysis of sorghum grain yields to prescribe incremental environmental and management changes (i.e. testing of model sensitivity to [CO_2], temperature, water, and N conditions). For this, we followed the CTWN protocol from AgMIP (crop responses to changes in carbon dioxide concentration ([CO2]), temperature, water, and nitrogen, Ruane et al. 2017). Using an average farm selected on the basis of the closeness of simulated yields with the observed median for both crop models, we varied CO_2 levels (360, 450, 540, 630, 720 ppm), temperatures (-2, 0, +2, +4, +6 and +8°C), rainfall (25, 50, 75, 100, 125, 150, 175 and 200%) and nitrogen application rates (N= 0, 30, 60, 90, 150, 180 kg ha^{-1}). These levels represent plausible changes in environmental conditions that make it possible to test the sensitivity of crop models (Rosenzweig et al., 2013, Franke et al. 2019).

Finally, to establish the relative magnitude of each factor (improved management versus future climate) on sorghum grain yields, we compared the effect of the intervention packages with the effect of future climates across farm strata. For current sorghum production systems, since fertilizers were not applied, the main differences between farms arose from variable soil properties and sowing dates.

Results

Ability of the models to reproduce yield variability

Table 4 shows that variability across farms (Vm) was greater than variability across years (Vw). The effect of management practices and soil (Vm) on grain yields amounted to 49% and 79% of variability in grain yields in the observed data for Koutiala and Navrongo, respectively. These variabilities were similarly simulated with both models for Koutiala, while for Navrongo, the observed variability is twice the simulated one by APSIM. With respect to weather, inter-annual variability (Vw) at both sites, APSIM appeared to simulate less variability in sorghum grain yields than DSSAT. The level of variability from year to year varied from 11% to 20%, thus Vw was less important compared to the variability associated with soil and management practices (from 49 to 79% in the observed data).

In Navrongo, the simulated sorghum grain yields from DSSAT ranged from 233 to 1208 kg ha^{-1}, with an average yield of 579 kg ha^{-1}, being slightly higher than the observed yields (Table 4). With APSIM, the simulated grain yields ranged from 315 to 843 kg ha^{-1}, with an average yield of 490 kg ha^{-1}. The simulated yield variability across farms (Vm) was 56% and 34% for DSSAT and APSIM, respectively, which was lower than the observed variability between farms (Table 4). In Koutiala, simulated sorghum grain yields from DSSAT ranged from 240 to 1357 kg ha^{-1}, with an average yield of 757 kg ha^{-1} and from 319 to 1498 from APSIM, with an average yield of 780 kg ha^{-1} among households. Variability across farms (Vm) was 38% and 42% for DSSAT and APSIM, respectively, similar to the observed variability among farms (Table 4).

TABLE 4

Effect of future climates on sorghum grain yield

Overall, the APSIM model simulated positive effects on sorghum grain yields for future climates for both sites (Figure 3). However, with the DSSAT model, the effect was largely negative in Koutiala, particularly for the warm cases (both wet and dry), and for some cases in Navrongo.

In Koutiala, yield changes under future climates assuming unchanged management ranged (DSSAT) from -38 to -8% on average (Figure 3). Simulated grain yields ranged from 524 kg ha^{-1} for the warmer to drier case and 667 kg ha^{-1} for the cooler and drier case under RCP 4.5, compared to the simulated baseline yield of 757 kg ha^{-1}. Under RCP 8.5, average yields ranged from 455 kg ha^{-1} (warmer/drier) to 616 kg ha^{-1} (cooler/wetter), confirming the expected stronger yield reductions under RCP 8.5, compared to RCP 4.5. Generally, warmer cases resulted in greater yield reductions. For APSIM, yield changes ranged from 0 to +7%. Simulated yields for future climates ranged fromc799 kg ha^{-1} (cooler/wetter) to 860ckg ha^{-1} (warmer/drier) under RCP 4.5, compared to the simulated baseline yield of 803 kg ha^{-1}. Under RCP 8.5, average yields ranged from 774 kg ha^{-1} (warmer/wetter) to 866 kg ha^{-1} (cooler/drier), representing more contrasting yield changes of -3 to +8%.

In Navrongo, yield changes under future climates assuming unchanged management either decreased or increased compared to the baseline, depending on the crop model and the GCM. DSSAT simulations indicated slight reductions for 4 out of 5 GCMs, ranging from +1% to -7% relative to the baseline yield of 572 kg ha^{-1}. Interestingly, the sole GCM featuring stable yield (+1%) corresponded to the warmer/drier case. Under RCP 8.5, yields ranged between 516 and 566 kg ha^{-1}, amounting to a reduction of 9 % for the cooler/wetter case vs. stable to marginal gains of between 0 to 4 % in the remainder. The warmer/wetter case recorded the lowest yields under RCP 4.5. In APSIM, all the GCMs simulated slight to moderate yield gains (RCP 4.5: 1-5%; RCP8.5: 5-10%) relative to the 480 kg ha^{-1} baseline (Figure 3). Under RCP 4.5, the highest yields (520 kg ha^{-1}) were predicted for the warmer/drier case, and the lowest yields for the cooler/wetter case.

FIGURE 3

Overall, the results suggested a stronger negative impact of future climates on sorghum grain yields in Koutiala compared to Navrongo (Figure 3). This difference was even larger with DSSAT simulations. APSIM almost never predicted yield decreases, while DSSAT did in most cases, and mostly in Koutiala. The differences in model output can partly be explained by their differences in the sensitivity to phenology, and partly by the level of intensification at the sites. While APSIM will extend phenology due to nutrient stress, phenology in DSSAT is not sensitive to nutrient stress. Additionally, the future projected climates indicated an extension of rains into dryer months (in the baseline weather). Hence, the simulations in APSIM benefited from the extended rainfall in the future climate (compared to the baseline climate), resulting mainly in positive yield changes that the DSSAT simulations did not benefit from.

The difference in yield impact between the two sites can also be explained by the fact that Koutiala is a relatively more intensive site with an average observed grain yield of 733 kg ha^{-1} compared to only 388 kg ha^{-1} for Navrongo. Looking at the overall simulation points (Figure 4), the results from DSSAT showed that the higher the simulated grain yield was, the lower was the probability of a large gain or reduction due to future climates (i.e. the variability in grain yield change diminished), regardless of the climate outcome (drier/wetter/cooler/warmer). Additionally, higher grain yields were associated with lower variability in yield changes (inter-annual and across farms) in future climates. With APSIM, the future variability in yield changes was also slightly reduced with higher simulated yields (Figure 4). This result suggested a greater sensitivity of low crop yield fields to future climates.

FIGURE 4

To further explain the differences between the two models, we conducted an analysis of grain yield sensitivity to key climatic variables and the level of nitrogen applications (Figure 5). While model responses to CO_2 (i.e. no response as expected for a C4 crop with low N input) and rainfall (i.e. water stress response when rainfall was reduced by a factor over 2) were similar (Figure 5a&b), DSSAT was more sensitive to temperature increases, with reduced grain yields starting as early as +2°C. For

APSIM, yield reductions were only observed for temperature increases of +8°C (Figure 5c). This protracted response of APSIM to rising temperature resulted in a marginal grain yield decline, whereas DSSAT yields declined sharply. Conversely, we found that APSIM was more sensitive to increased nitrogen fertilization rates, with a clear response in sorghum grain yields from 800 kg ha^{-1} to 4 t ha^{-1} (Figure 5d). These results will be further addressed later to explain the model differences in the discussion section.

FIGURE 5

Effect of improved management on sorghum grain yields

In the current climate in Koutiala, shifting to the proposed improved variety demonstrated marginal effects on grain yields, regardless of which crop model was used (Figure 6). Meanwhile, increased fertilization rates and planting density boosted average grain yields by 20% in DSSAT and 153% in APSIM (Figure 6). For Navrongo, improved agronomy (higher fertilization rates and planting densities) resulted in average grain yields of 1616 kg ha^{-1} (DSSAT) and 1539 kg ha^{-1} (APSIM), respectively corresponding 256% and 236% gains over the baseline yields (Figure 6). The addition of genetic improvement resulted in further average yield increases of 12 and 24% for DSSAT and APSIM respectively.

The difference in yield impact between the two sites due to improved agronomy can partly be explained by the difference in the observed absolute crop yield level at both sites (Figure 1b). In Koutiala, the average observed grain yield was 733 kg ha^{-1} (with a maximum yield of 1942 kg ha^{-1}) compared to an average of 388 kg ha^{-1} (with a maximum yield of 1090 kg ha^{-1}) for Navrongo. Further, we can see in Figure 1b that Navrongo had a higher frequency of lower yields than Koutiala, re-enforcing the higher percentage yield change in Navrongo than in Koutiala. Indeed, in Navrongo the response to higher fertilization rates was greater than that in Koutiala, because the yield gap was already higher, mainly due to the lower fertility and shallower soil depth.

FIGURE 6

Our study showed that, in the current sorghum production systems, management practices have more effect on grain yield than the potential effect of future climates. It appeared that, whatever the crop model used, the benefits of improved management practices (increased fertilizer rates, improved planting density) will always be greater than the effect of future climates.

However, Figure 7 shows the yield change due to future climates in relation to the yield change resulting from improved management for all the simulated data points, according to soil types, future climate cases, and crop models. The red dashed line is the critical region below which positive yield changes arising from improved management could not compensate for the potential yield losses due to future climates. When comparing all yield changes (not averages) in the current production systems due to future climates and those due to improved management, we found that yield changes due to management practices did not always offset the yield changes due to climate change (Figure 7). The ability of changes due to management practices to offset those due to climate change depended on the soil type. For almost all the simulations with APSIM (except in very few cases), the changes due to improved management will compensate for the negative yield change due to future climates. With the simulations from DSSAT, the picture was slightly different. Although, in most cases, the yield changes due to improved management were greater than the negative yield changes due to future climates (above the red line), a small proportion of the data points still remained below the red dashed line. We found this was mostly the case for soils with a higher level of initial nitrogen (ITML840104, ITML840107, ITML840106, and ITML840102, Table 1 and Figure 7). These results suggested that soils with low fertility (most of the cases in West Africa) would be more responsive to the recommended improved management practices. On better soils, we found that the effect of improved management would not increase sorghum grain yields well enough to compensate for the potential effect of future climates. This further supported our findings in Figure 4, which showed that at potential low-yield sites future climate effects could vary greatly and there was a need to first get the management practices right before being able to understand the effect of future climates on sorghum grain yields. No major differences in the effect of improved management were observed according to sowing dates (data not shown).

FIGURE 7

Discussion

Multi-farm assessment study: choice of scale and model

The agricultural modeling community has developed climate impact protocols and conducted multiple inter-comparisons of models to evaluate and demonstrate applications within the Agricultural Model Inter-comparison and Improvement Project (AgMIP; Rosenzweig et al., 2013; Ruane et al., 2017). The same methodology was applied in this study to (i) conduct a multi-farm level assessment of the impact of climate change to capture farm heterogeneity, taking into account differences in crop management practices and soils (Freduah et al. 2019), as well as (ii) comparing different crop model simulations (Asseng et al., 2013; Bassu et al., 2014; Li et al., 2015).

This analysis revealed that the variability among farmers was greater than the variability due to intra-annual weather variability (Table 4), supporting previous studies showing the high intra-village variability of crop yields (Traoré et al. 2011). This variability in grain yields was the consequence of the different soil types and management practices captured in the household surveys. This was an important result for being able to identify where the effect of future climates on sorghum grain yields was strongest, thus aiding in targeting management strategies according to the context. We demonstrated that for soils with higher initial N, the effects of improved management were likely to be lower relative to those with low initial N, especially when using the DSSAT model (almost all simulations were under the red dashed line in Figure 7 for those soils). For simulations with APSIM, the effects of improved management were also evident, but to a lesser extent on those soils with higher initial N than the others. Hence, the future climate effect on sorghum grain yields might be greater or more visible than the effect of improving crop management when soil fertility is higher (Dimes et al. 2009). This result confirmed the outputs from a regional study by Faye et al. (2018), which concluded that under intensification scenarios, yield losses due to climate change will be higher for maize and sorghum than yield losses under the current production systems. However, it is key to note that regional studies (Faye et al., 2018; Sultan et al. 2014) usually use climate, soil, and crop management inputs that can cause uncertainties in crop model outputs, due to a lack of information about the local context (i.e. diversity of soils, diversity of varieties, and management practices). It remains important to be able to properly define the diversity of conditions (cultivar, soil, management practices) on global and regional scales. Faye et al., (2018) and Gbegbelegbe et al. (2017) already demonstrated the importance of considering different cultivars to capture yield variability at regional and global level. In this study, we added the importance of considering soils and management practices too, reflecting the farm heterogeneity existing in the West Africa region.

Model differences and improvement

Another advantage in applying this methodology was the use of two different crop models to evaluate the level of uncertainty in our assessment. The uncertainty of the simulation outputs for a given crop model is related to differences in model sensitivity to temperature, CO_2, rainfall, and N. Our study indicated that DSSAT had high sensitivity to temperature, while APSIM responded more strongly to nitrogen application (Figure 5), confirming the results of Faye et al. (2018). Such model behavior explains the minor response of APSIM to future climates, while with DSSAT, in most cases, we simulated a negative effect of future climates, due mostly to an increase in temperature, resulting in yield losses in the warmer future climate cases. Bassu et al (2014) also demonstrated that the negative response of maize yields to rising temperatures could be a significant challenge for local food production. Likewise, the literature (Sultan et al.,2013, Faye et al. 2018) showed that sorghum grain yield losses increased as temperatures increased, confirming the important role of this factor in reducing crop yields, as simulated by DSSAT in this study. The difference in model outputs could be attributed to differences in the optimum temperature functions used for sorghum in the two models. In the version of the models used for this study, DSSAT stopped the photosynthesis process when the temperature reached 44°C, while for APSIM the threshold temperature was 50°C. Further, to create a more heat-tolerant cultivar, we changed the upper threshold value to the response curve of the effect of temperature on relative grain filling rate in DSSAT, while with the version of APSIM that we used (v.7.5) the effect of high temperature shock on seed set was not yet included. Interaction during this work with APSIM modelers did indeed lead to improvement of the model, with the addition of CO_2 , fertilization effects and the effect of high temperature shock on seed set for version 7.10. These different responses of the two crop models to environmental variables (temperature, nitrogen, water) call for care in the choice of models and model improvements when carrying out a climate impact assessment study and reinforce the importance of justification for the use of a particular crop model for a study (Challinor et al., 2018). Many climate change impact assessment studies have been carried out in the West Africa region with different crop models (Amouzou et al., 2019; Faye et al., 2018; Roudier et al., 2012; Sultan et al., 2014; Traore et al., 2017, this study), but there is rarely a clear explanation for the choice of the model used, and whether the version of the crop model used included the key elements discussed here. For low input cropping systems, it also appears essential to choose crop models that can accurately simulate nitrogen dynamics and responses to crop phenology, and also ensure that they have been properly tested.

Recommendation for action: better agronomy rather than breeding

While trying to capture climate model uncertainty (Corbeels et al. 2018) by including 10 different future climates (5GCM * 2 RCP), we can still conclude that sorghum, as it is cultivated today, is moderately vulnerable to future climates (compared to improved management, Figures 3 and 6). In addition, we showed that the higher the simulated grain yields were, the less variability there was in simulating the effect of future climates on sorghum grain yields, irrespective of the climate cases. This suggests a need to explore the increase in sorghum yields through improved agronomic practices, before thinking about the effect of climate change. In other words, if farmers maintain their current management practices and yield levels, climate change will be largely inconsequential due to the over-riding constraint of fertility on crop yields (Dimes et al. 2009). There is an urgent need to improve sorghum productivity by improving access to inputs through subsidies (Falconnier et al. 2018). With this research, we clearly showed the importance of management practices that outweigh the impact of climate change on sorghum in the semi-arid region of West Africa. To reinforce this statement, the simulation outputs, independent of the crop models used, clearly showed the strong effect of improved management practices on sorghum grain yields (Figure 6). We can say that doubling fertilizer inputs today, with adjusted planting densities, will more than double sorghum yields, and that increasing smallholder use of fertilizers and improved management practices is more important today than improved varieties (Figure 6). The percentage increases in yields were within those reported by other studies in similar environments. An on-station study by Naab et al. (2015) reported a high N response (increases) of 314% in maize yields averaged over 4 years when comparing yields without N fertilizer with those that received 60 kg N ha^{-1}. Similarly, in on-farm research carried out by MacCarthy et al. (2009), sorghum yields increased from an average of 705 kg ha^{-1} without N fertilizer applications to an average of 2212 kg ha^{-1} with the application of 40 kg N ha^{-1} on a bush farm, which resulted in roughly a 214% increase in sorghum yields.

Further, we showed that the additional effect of using an improved cultivar resulted in a relatively lower yield increase compared to the intervention package without improved cultivar use. This was probably because the farming systems in this study area were under-optimized. However, with expected socio-economic changes and assumable greater investment in soil quality (Dimes et al. 2009, Falconnier et al. 2018), drought or heat tolerant varieties might become more important under future climates. Hence, there is an urgent need to prioritize better agronomy in these systems. As Giller et al. (2017) mentioned, improving crop cultivars will widen the yield gap, hence we need to focus first on better agronomy to address the immediate needs for crop yield improvement, given that improved cultivars can only perform under good management practices. However, we should not fall into the trap of just advising better agronomy. It is essential to target our recommendation according to the context and adapt management practices according to the heterogeneity of farms. As shown in this research, improved management has more impact on poor soils than on good soils, and the effect of future climates seemed more variable in the low potential sites. Hence, it is important to target those sites first to improve current crop yields. In addition, even though we only looked at the biophysical aspects that can improve crop yields in this research, the heterogeneity found on the farms we studied (i.e. the context) was also the reflection of socio-economic circumstances (i.e. access to fertilizers), which should be considered in further studies. As indicated by Tittonell et Giller (2013) "*The lack of immediate response to increased inputs of fertilizer and labour in such soils constitutes a chronic poverty trap for many smallholder farmers in Africa"* (p79).

Concluding remarks

Many studies in the literature (Sultan et al. 2014, Challinor et al.2014, Faye et al. 2018) have shown that climate change will undeniably affect crop productivity in West Africa. However, our study showed that this statement needs to be taken with caution, especially for sorghum crops. In this multi-farm *ex-ante* assessment at local level, we showed that sorghum is a climate-resilient crop, with future climates having little effect on its yields. However, there is an urgent need for better agronomy to boost its yields in the semi-arid regions of West Africa. The results of the study showed that not only will (1) a change in management practices (such as the addition of fertilizers and planting density) more than double grain yields, but also (2) that inter-farm yield variability is greater than inter-annual weather variability. Further, for *ex-ante* analysis and in particular for the climate change study, it is important to consider the choice of crop model, as this study revealed the high sensitivity of DSSAT to temperature, while APSIM responded more strongly to nitrogen application. This will be very important to take into consideration when interpreting results, as uncertainty from model outputs needs to be considered when conveying a message to stakeholders. In the current sorghum production systems in the semi-arid regions of West Africa, our study clearly showed (irrespective of the crop models) that the effect of management practices was greater than the effect of future climates on sorghum grain yields.

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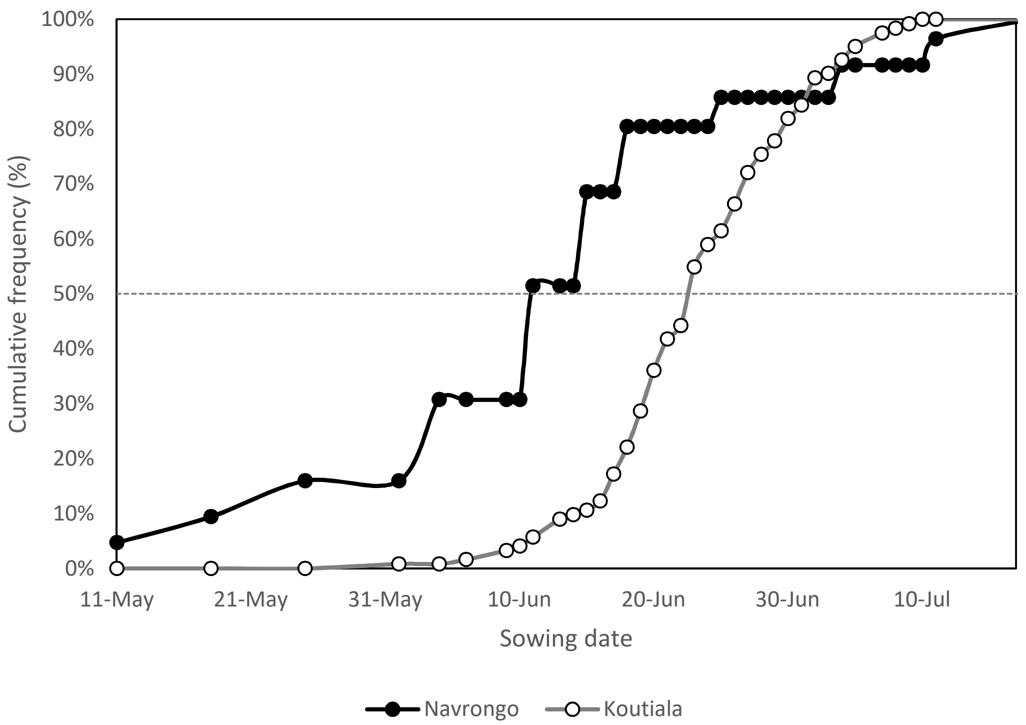
Figure 1: Sowing dates cumulative frequency (A) and observed sorghum grain yield frequency (B) for both study sites, showing earlier sowing in Navrongo than in Koutiala; and higher frequency of low grain yield in in Navrongo than in Koutiala.

A



B

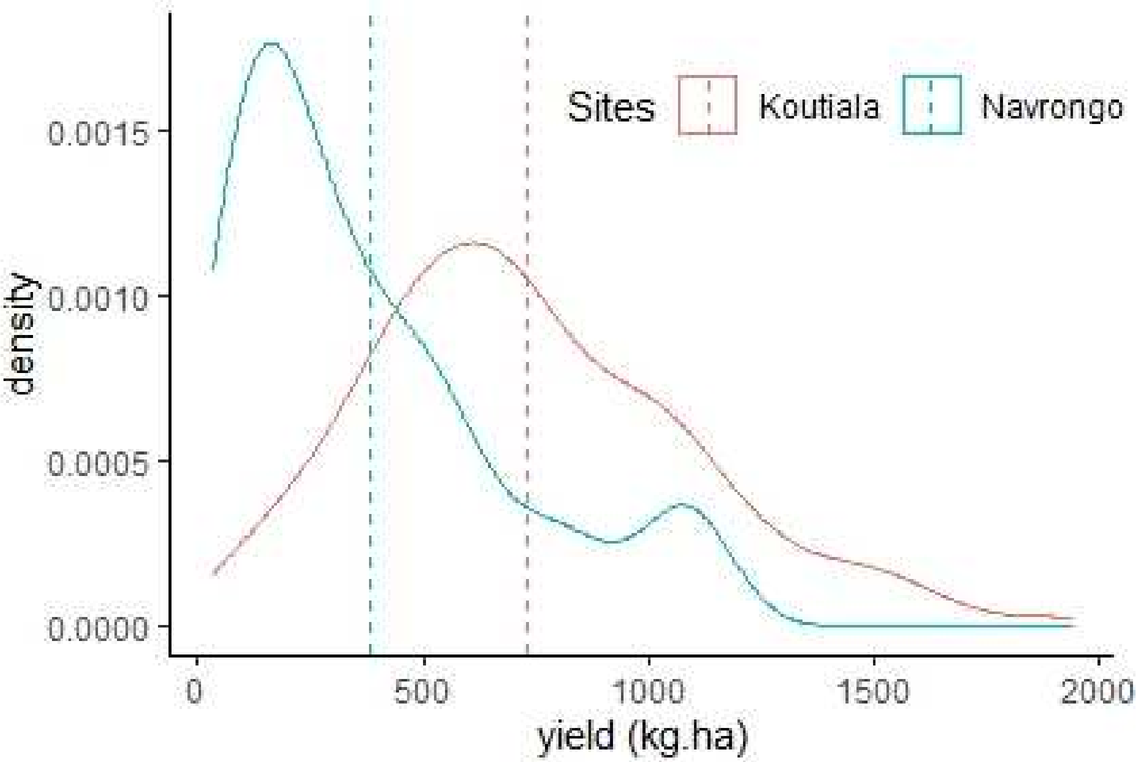


Figure 2: Scatterplot of change in temperature and precipitation in JJAS period describing the AgMIP criteria of the selection of the 5 GCMs in Navrongo station in Ghana, Koutiala (Mali). In green are climate scenario classified as relatively cooler and wetter than the average; in blue scenario relatively cooler and drier; in yellow relatively hotter and wetter; in red relatively hotter and drier; and in black average scenario (middle). The numbers correspond to the number of climate scenario in each categories (i.e. cool-wet). Letters corresponds to a specific GCM (*A:ACCESS1-0/ B:bcc-csm1-1/ C:BNU-ESM/ D: CanESM2/ E: CCSM4/ F: CESM1-BGC/ G: CSIRO-Mk3-6-0/ H: GFDL-ESM2G/ I: GFDL-ESM2M/ J: HadGEM2-CC/ K: HadGEM2-ES/ L: inmcm4/ M: IPSL-CM5A-LR/ N: IPSL-CM5A-MR/ O: MIROC5/ P: MIROC-ESM/ Q: MPI-ESM-LR/ R: MPI-ESM-MR/ S: MRI-CGCM3/ T: NorESM1-M*)

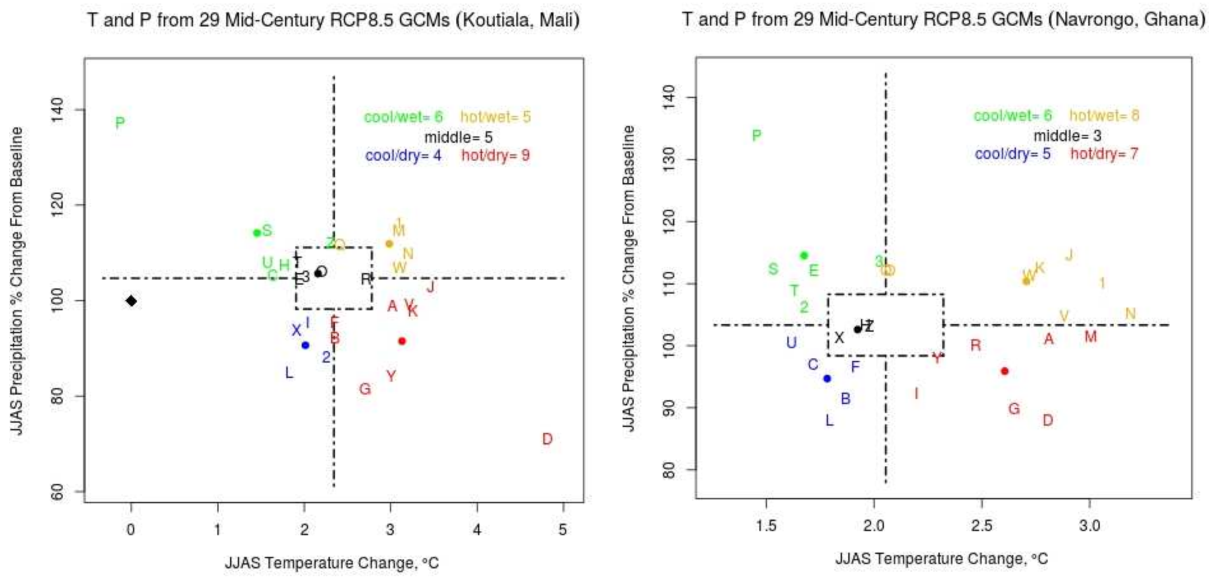


Figure 3: Climate change impact (in percent of change) on sorghum productivity simulated by two crop models (APSIM and DSSAT) for the current systems in Koutiala and Navrongo.

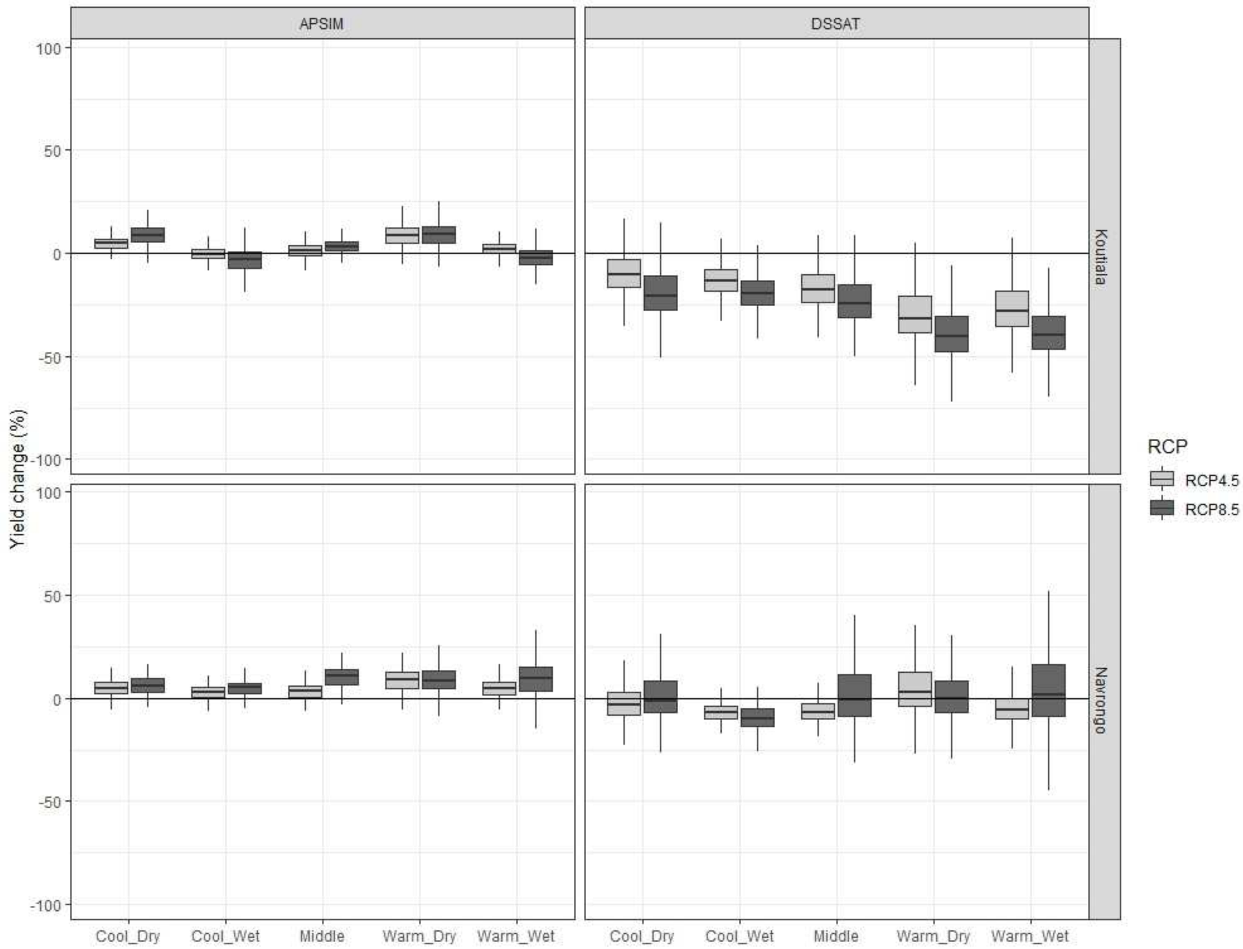


Figure 4: Response of yield change (%) relative to baseline grain yield (kg.ha^{-1}) for all climate scenario and all sites for two RCP simulated by two crop models (APSIM, DSSAT).

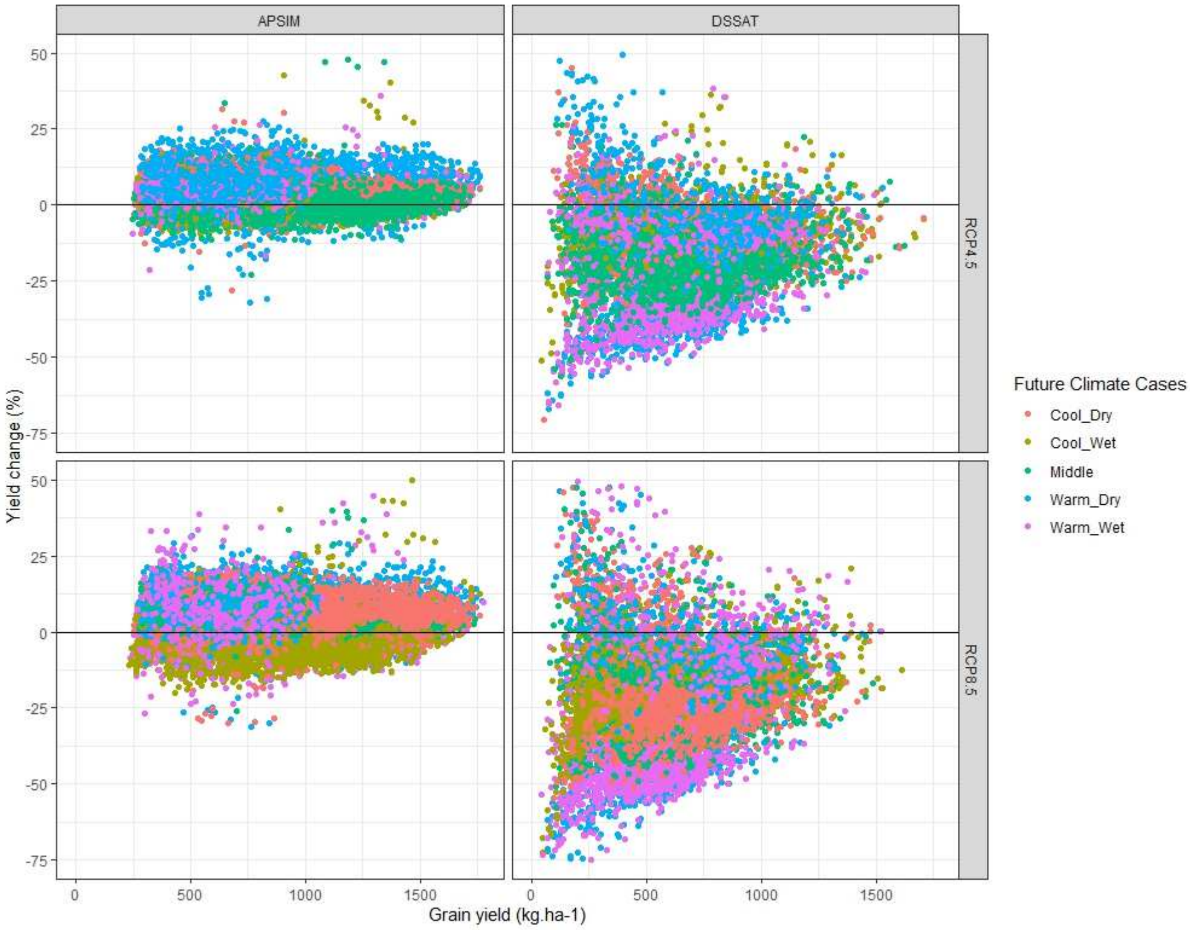


Figure 5: Sensitivity of the crop models to CO_2, temperature, water/rainfall, and nitrogen (CTWN) in Koutiala, Mali: a. Response to elevated CO_2 under 180 kg N ha^{-1} fertilizer applied, b. response to rainfall changes, c. Response to temperature changes, d. response to N application. The boxplots represent the inter-annual variability simulated by APSIM (red) and DSSAT (blue), while the lines repesent the mean sorghum grain yield simulated by APSIM (yellow) and DSSAT (green).

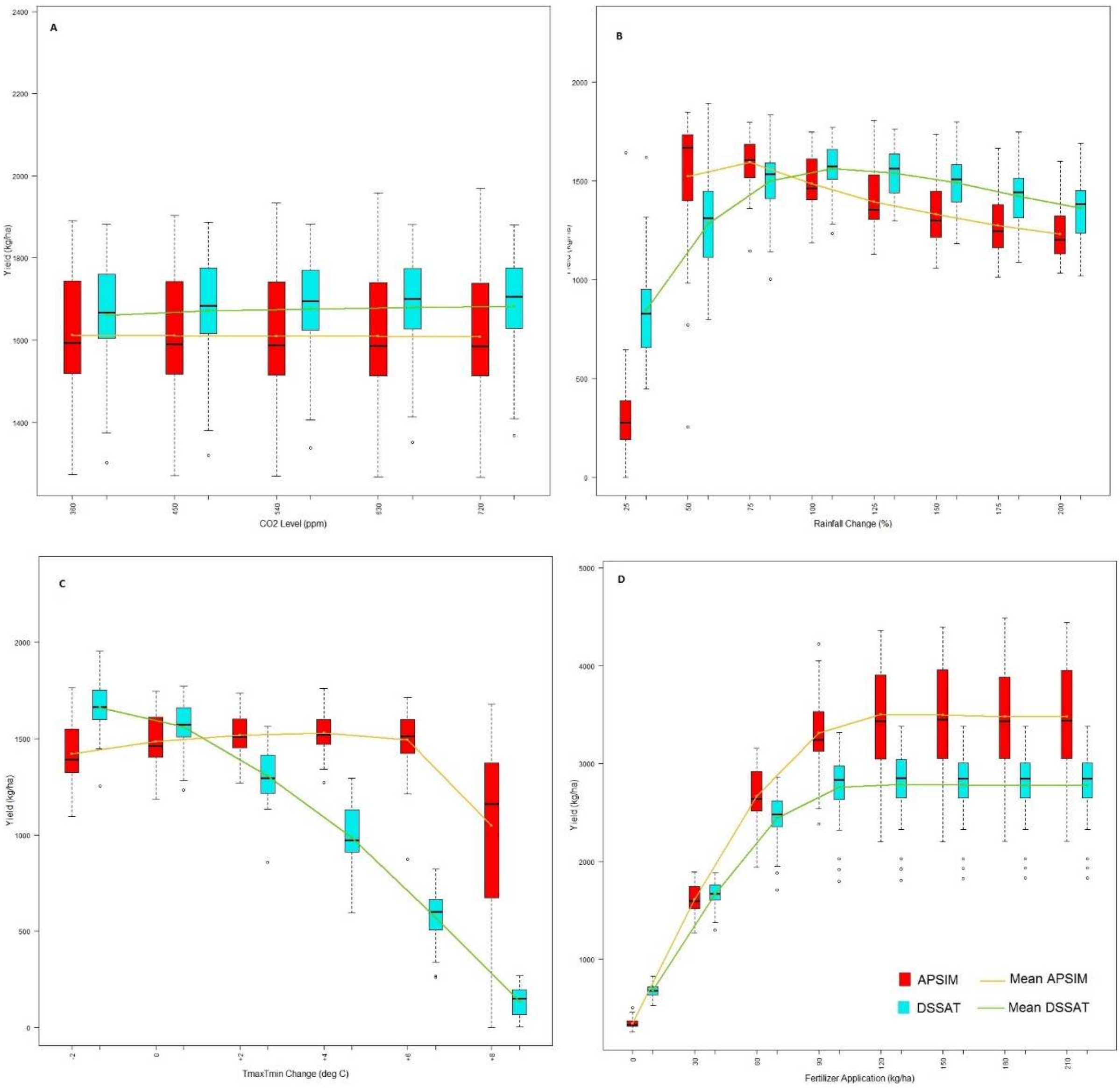


Figure 6: Yield changes for sorghum grain in percent simulated by two crop models (APSIM and DSSAT), for different intervention packages under current climate at Navrongo and Koutiala study sites.

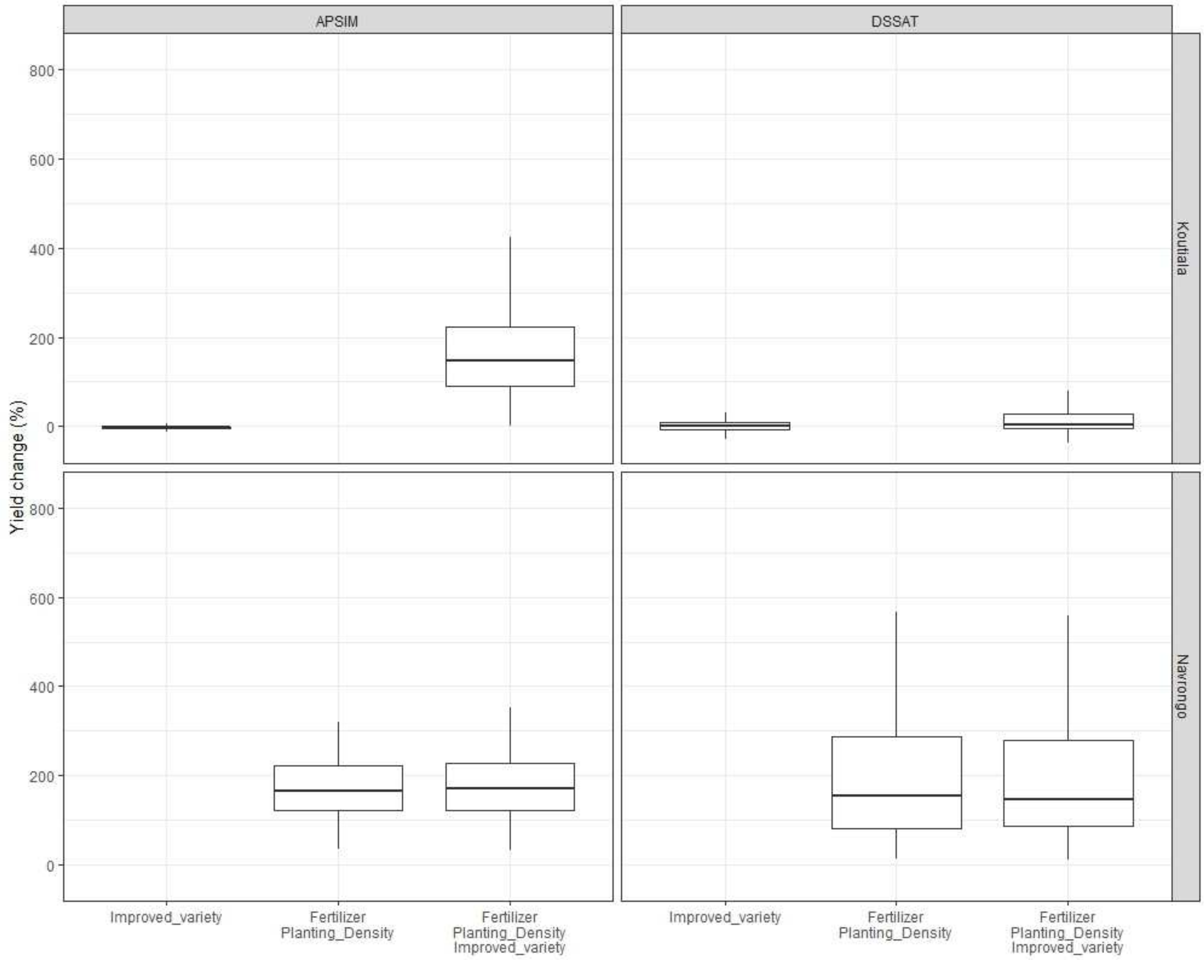


Figure 7: Yield change due to climate change vs yield change due to intervention packages yield for all climate scenarios simulated by two crop models, represented by soil type. The red dashed line represents the limit beyond which increases due to intervention packages can compensate (over the line) the potential effect of climate change on the current cropping systems.

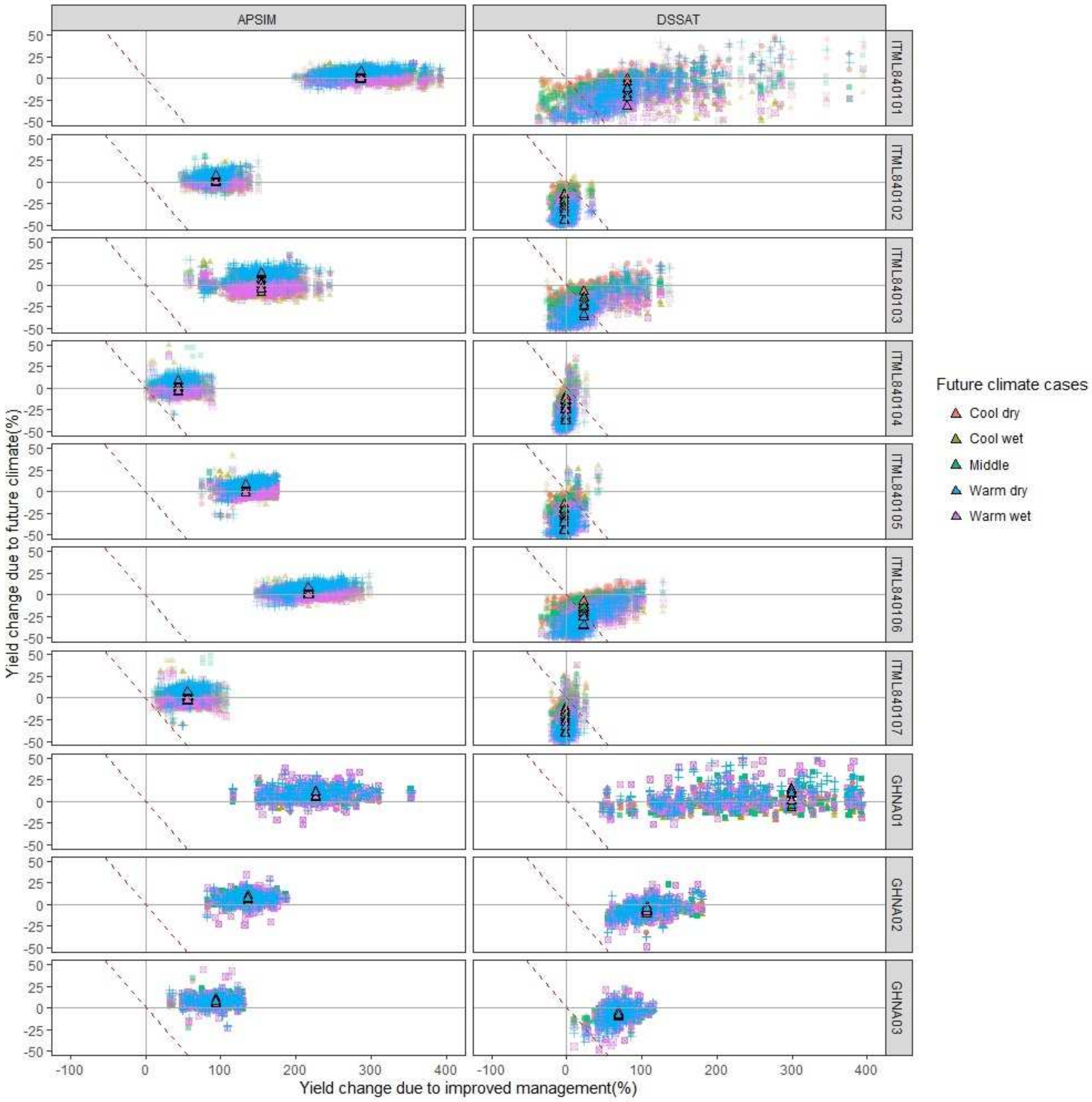


Table 1. Soil parameters used in simulations for the Navrongo, Ghana, and Koutiala Mali. The shaded soils are soils with higher initial N.

Location	Soil ID	L (cm)	SLL (cm^3/cm^3)	SDUL (cm^3/cm^3)	SAT (cm^3/cm^3)	BD (g/cm^3)	OC (%)	pH	NH4 (mg/kg)	NO3 (mg/kg)
Navrongo	GHNA01	5	0.052	0.176	0.352	1.43	0.3	5.5	1	0.5
		15	0.052	0.176	0.352	1.43	0.3	5.5	1	0.5
		30	0.052	0.176	0.321	1.45	0.29	5.3	0.5	0.5
		50	0.073	0.192	0.32	1.45	0.25	5.3	0.5	0.5
	GHNA02	5	0.082	0.213	0.352	1.56	0.39	6.2	1	0.5
		15	0.082	0.213	0.352	1.56	0.39	6.2	1	0.5
		30	0.09	0.209	0.321	1.58	0.36	5.9	0.5	0.5
		50	0.11	0.205	0.32	1.56	0.32	5.9	0.5	0.5
	GHNA03	5	0.054	0.131	0.353	1.67	0.58	5.1	2	0.5
		15	0.054	0.131	0.353	1.67	0.58	5.1	1	0.5
		30	0.094	0.119	0.359	1.74	0.56	5.4	1	0.5
		50	0.106	0.192	0.369	1.83	0.45	5.3	0.5	0.5
Koutiala	ITML840101	10	0.05	0.15	0.45	1.39	0.2	5.4	0.05	0.5
		25	0.05	0.15	0.45	1.39	0.2	5.4	0.05	0.5
		60	0.123	0.234	0.417	1.48	0.1	6.2	0.05	0.5
		110	0.181	0.283	0.406	1.51	0.1	5.8	0.05	0.5
	ITML840102	10	0.153	0.271	0.427	1.45	0.448	5.6	0.3	1.5
		45	0.153	0.271	0.427	1.45	0.448	5.6	0.3	1.5
		70	0.173	0.302	0.438	1.42	0.372	5.3	0.3	1.5
		100	0.172	0.3	0.438	1.42	0.343	5.3	0.3	1.5
	ITML840103	16	0.056	0.117	0.395	1.54	0.29	5.5	0.3	0.7
		23	0.089	0.151	0.374	1.6	0.26	5.4	0.3	0.7
		32	0.106	0.17	0.367	1.62	0.25	5.6	0.3	0.7
		57	0.122	0.183	0.36	1.64	0.19	5.7	0.3	0.7
		83	0.117	0.179	0.364	1.63	0.15	5.9	0.3	0.7
		110	0.114	0.174	0.361	1.64	0.14	5.9	0.3	0.7
		135	0.117	0.179	0.364	1.63	0.13	8.2	0.3	0.7
		150	0.104	0.164	0.361	1.64	0.12	8.3	0.3	0.7
		160	0.105	0.17	0.368	1.62	0.12	8.4	0.3	0.7

Location	Soil ID	L (cm)	SLL (cm^3/cm^3)	SDUL (cm^3/cm^3)	SAT (cm^3/cm^3)	BD (g/cm^3)	OC (%)	pH	NH4 (mg/kg)	NO3 (mg/kg)
Koutiala	ITML840104	7	0.087	0.184	0.437	1.41	0.91	6.4	0.5	2
		16	0.091	0.174	0.407	1.5	0.6	5.9	0.5	2
		30	0.165	0.255	0.4	1.52	0.6	5.2	0.5	2
		40	0.22	0.32	0.411	1.49	0.54	5.1	0.5	2
		54	0.24	0.343	0.416	1.48	0.46	5.2	0.5	2
		68	0.249	0.356	0.427	1.45	0.41	5.3	0.5	2
		105	0.207	0.301	0.399	1.53	0.32	5.4	0.5	2
	ITML840105	10	0.066	0.139	0.405	1.51	0.384	6.3	0.2	1
		20	0.066	0.139	0.405	1.51	0.384	6.3	0.2	1
		35	0.086	0.162	0.392	1.55	0.273	5.4	0.2	1
		50	0.133	0.22	0.389	1.56	0.221	5.4	0.2	1
		70	0.22	0.316	0.4	1.53	0.221	5.4	0.2	1
		120	0.242	0.341	0.411	1.5	0.157	5.8	0.2	1
	ITML840106	10	0.05	0.15	0.45	1.39	0.3	5.4	0.1	0.7
		25	0.05	0.15	0.45	1.39	0.3	5.4	0.1	0.7
		60	0.123	0.234	0.417	1.48	0.2	6.2	0.1	0.7
		110	0.181	0.283	0.406	1.51	0.1	5.8	0.1	0.7
	ITML840107	7	0.087	0.184	0.437	1.41	0.8	6.4	0.5	1.8
		16	0.091	0.174	0.407	1.5	0.5	5.9	0.5	1.8
		30	0.165	0.255	0.4	1.52	0.5	5.2	0.5	1.8
		40	0.22	0.32	0.411	1.49	0.4	5.1	0.5	1.8
		54	0.24	0.343	0.416	1.48	0.3	5.2	0.5	1.8
		68	0.249	0.356	0.427	1.45	0.3	5.3	0.5	1.8
		105	0.207	0.301	0.399	1.53	0.2	5.4	0.5	1.8

L = Depth of the soil layer, SLL = soil lower limit or wilting point, SDUL = soil drained upper limit or field capacity,SAT = saturated water content, BD = bulk density, OC = organic carbon.

Table 2. Model parameters of Sorghum used in simulations. Values with a * are values of parameters that did not change for our virtual cultivars; and in bold the ones that changed.

Model	Codes	Definitions	ICSVII		CSM335	
			baseline	improved	baseline	improved
DSSAT	P1	Thermal time from seedling emergence to the end of the juvenile phase during which the plant is not responsive to changes in photoperiod (expressed in degree days).	470	**376**	450	**495**
	P5	Thermal time from beginning of grain filling to physiological maturity (expressed in degree days).	620	**744**	440	**484**
	PHINT	Phyllochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	65.0	65.0*	60	60*
	P2O	Critical photoperiod or the longest day length (in hours) at which development occurs at a maximum rate. At values higher than P2O, the rate of development is reduced.	12.6	12.6*	12.6	12.6*
	P2R	The extent to which phasic development leading to panicle initiation (expressed in degree days) is delayed for each hour increase in photoperiod above P2O.	0.01	0.01*	500	500*
	G1	Scaler for relative leaf size	21.0	21.0*	0.8	0.8*
	G2	Scaler for partitioning of assimilates to the panicle (head)	7.0	**8.4**	1.0	**1.2**
		Duration – emergence to end of juvenile	100	**120**	220	**242**
APSIM		Duration – end of juvenile to panicle initiation	280	280*	140	140*
		Duration – flag leaf to flowering stage	231	231*	170	170*
		Duration, flowering to start of grain filling	59	**70.8**	80	**88**
		Duration, flowering to maturity	650	650*	420	420*
	dm_per_seed	Grain number determination (g/grain)	0.00083	**0.00099**	0.00083	**0.00099**

Table 3. List of the selected GCMs for Navrongo (Ghana), Koutiala (Mali) according the AgMIP protocol.

Navrongo, Ghana					
	Cool/Wet	Hot/Wet	Middle	Cool/Dry	Hot/Dry
RCP8.5	CCSM4	CMCC-CMS	GFDL-ESM2	BNU-ESM	MPI-ESM-MR
RCP4.5	CCSM4	CMCC-CM	MRI-CGCM3	bcc-csm1-1	CMCC-CMS
Koutiala, Mali					
	Cool/Wet	Hot/Wet	Middle	Cool/Dry	Hot/Dry
RCP8.5	MIROC5	ACCESS1-0	GFDL-CM3	MPI-ESM-MR	CCSM4
RCP4.5	CCSM4	ACCESS1-0	MRI-CGCM3	CMCC-CMS	CESM1-BGC

Table 4. Source of variation in observed and simulated baseline sorghum grain yield among farms (Vm) and due to inter-annual weather variability (Vw) at Koutiala and Navrongo sites.

Region		Grain yield in $kg.ha^{-1}$ (range)	Vm	Vw
Koutiala	Observed	733 (90-1942)	49%	-
Koutiala	APSIM	780 (319-1498)	42%	12%
Koutiala	DSSAT	757 (240-1357)	38%	17%
Navrongo	Observed	388 (33-1090)	79%	-
Navrongo	APSIM	490 (315-843)	34%	11%
Navrongo	DSSAT	579 (233-1208)	56%	20%