Intensifying Maize Production Under Climate Change Scenarios in Central West Burkina Faso

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Abstract

Combination of poor soil fertility and climate change and variability is the biggest obstacle to agricultural productivity in Sub-Saharan Africa. While each of these factors requires different promising adaptive and climate-resilient options, it is important to be able to disaggregate their effects. This can be accomplished with ordinary agronomic trials for soil fertility and climate year-to-year variability, but not for long-term climate change effects. In turn, by using climate historical records and scenario outputs from climate models to run dynamic models for crop growth and yield, it is possible to test the performance of crop management options in the past but also anticipate their performance under future climate change or variability. Nowadays, the overwhelming importance given to the use of crop models is motivated by the need of predicting crop production under future climate change, and outputs from running crop models may serve for devising climate risk adaptation strategies. In this study we predicted yield of one maize variety named Massongo for the time periods 1980–2010 (historical) and 2021–2050 (2030s, near future) across agronomic practices including the fertilizer input rates recommended by the national extension services (28 kg N, 20 kg P, and 13 kg K ha^{-1}). The performance of the crop model DSSAT 4.6 for maize was first evaluated using on-farm experimental data that encompassed two seasons in the Sudano-Sahelian zone in six contrasting sites of Central West Burkina Faso. The efficiency of the crop model was evidenced by reliable simulations of total aboveground biomass and yields after calibration and validation. The root-mean-square error (RMSE) of the entire dataset for grain yield was 643 kg ha^{-1} and 2010 kg ha^{-1} for total aboveground biomass. Three regional climate change projections for Central West Burkina Faso indicate a decrease in rainfall during the growing period of maize. All the three scenarios project that the decrease in rainfall is to the tune of 3–9% in the 2030s under RCP4.5 in contrast to climate scenarios produced by the regional climate model GCM ICHEC-EC-Earth which predicted an increase of rainfall of 25% under RCP8.5. Simulations using the CERES-DSSAT model reveal that maize yields without fertilizer show the same trend as with fertilizer in response to climate change projections across RCPs. Under RCP4.5 with output from the climate model ICHEC-EC-Earth, yield can slightly increase compared to the historical baseline on average by less than 5%. In contrast, under RCP8.5, yield is increased by 13–22% with the two other climate models in fertilized and non-fertilized plots, respectively. Nevertheless, the average maize yield will stay below 2000 kg ha^{-1} under non-fertilized plots in RCP4.5 and with recommended mineral fertilizer rates regardless of the RCP scenarios produced by ICHEC-EC-Earth. Giving the fact that soil fertility improvement alone cannot compensate for the adverse impact of future climate on agricultural production particularly in case of high rainfall predicted by ICHEC-EC-Earth, it is recommended to combine various agricultural techniques and practices to improve uptake of nitrogen and to reduce nitrogen leaching such as the splitting of fertilizer applications, low-release nitrogen fertilizers, agroforestry, and any other soil and water conservation practices.

Keywords
DSSAT 4.6 · Climate change projection · Site-specific fertilization · Validation

Introduction

As the planet warms, climate change predictions increasing mean surface air temperatures from 2 °C to 5 °C by the end of the century are considered robust for West Africa, whereas no consensus has emerged on how precipitation is likely to evolve (Christensen et al. 2007; Cooper et al. 2008). Meanwhile, there seems to be an agreed perception about the exacerbation of intra-seasonal variability and rainfall patterns shift that future climate is likely to be characterized by Sylla et al. (2016) and Roudier et al. (2011). This may lead to lowering or unpredictable crop yield resulting in food insecurity especially in Sudanian zone of West Africa where farmers are the most vulnerable (Zoellick 2009). Although great efforts have been deployed in the research on the nexus climate change-agriculture, these were focused on evaluating the sensitivity of various cropping systems to pest, diseases, weeds, etc. (Enete and Amusa 2010). Less has been done on anticipating the effects of rainfall variability in order to cope with the negative effects of climate change and variability.

Globally, the national development programs tend to focus on more “high-tech” solutions to increasing food production such as increasing subsidies of mineral fertilizers and promoting improved seeds and equipment. However, the potential benefits of these approaches will be undermined unless the depletion of soil fertility is reversed and climate change impacts are overcome (Winterbottom and Reij 2013). Therefore, it is important to evaluate cropping systems under various environmental and climatic conditions including drought, nitrogen, and phosphorus-depleted soils as our study site located in Central West Burkina Faso. Soils in this area are usually relatively well weathered with low fertility which combined with high rainfall variability induce poor crop yields. Like in other Sub-Saharan countries, the low use of fertilizers especially the most important nutrients (nitrogen, phosphorous, and potassium) is considered as a major constraint to increasing productivity (Bationo et al. 1998; Samaké et al. 2005; Tadele 2017). As a consequence the extension staff tend to only promote the use of fertilizers, ignoring adaptive measures to climate change or variability for high yield crop production. Indeed, there is a need for information about the potential impact of climate change on agricultural systems in the future, and this is currently tackled by applying physiology-based crop simulation models (Asseng et al. 2013). As those crop models are used to predict variability of crop yield and related variables as well as natural resource use from driving factors such as short- and long-term variation of weather and climate conditions, linking climate-induced risk with yield gap analysis might seem relevant to predict crop yields in the future. To do so, these models need to be thoroughly tested and validated for given site/region to establish their credibility (Boote et al. 1996). Gaiser et al. (2011) recommended detailed site-specific soil input parameters (e.g., organic matter pools, water retention) for reliable prediction of scenario effects for individual sites. Bassu et al. (2014) found that increasing the level of input information (i.e., high information in calibration) significantly reduced the uncertainties in the models' outputs. In the present study, we utilized DSSAT model which has been successfully tested under water- or nutrient-limited production conditions in West Africa over a wide range of crops and management options (Fatondji et al. 2010). Most of the past trials of this model have used on-station data, thus unable to capture the real conditions of the farmers, except few cases in agroforestry with other models (Bayala et al. 2008; Coulibaly et al. 2014; Luedeling et al. 2016). Our study is a contribution to fill in that gap by using on-farm data as they better represent farmers' real conditions.

The objective of this study was to assess the impacts of climate change on agronomic productivity of maize (*Zea mays*) by using crop growth model simulation based on historical climate records (1981–2010) and bias-corrected near-future (2021–2050) climate projections for the Central West Burkina Faso. In this study, the key research questions were to find out (1) whether DSSAT crop model can reliably predict maize production under smallholder farming conditions in the Sudan Savanna of West Africa with and without fertilizer application and (2) what are the impacts of climate change on the production risk of maize for these cropping systems when fertilizer is applied or omitted. The hypothesis tested is that conventional intensification (high mineral N supply), reported to sustain yield under various climate scenarios (Folberth et al. 2014) at the continental scale, is negatively affected by the projected future climate change in Burkina Faso.

Materials and Methods

Study Sites, Experiment Description, and Data Collection

The agronomic trials were carried out in farmers' fields in three villages, Cassou, Dao, and Kou, from the departments of Cassou, Gao, and Bakata, respectively, located in Ziro Province of the Central West Burkina Faso (11°42′N, 2°03′W) (Fig. 1). The average altitude of Ziro Province is about 300 m a.s.l., and this province lies within the South-Sudanian ecological zone (Fontes and Guinko 1995) and receives 900–1200 mm rainfalls annually. Its unimodal rainy season lasts for about 6 months, from May to October. According to the FAO's soil classification system (Driessen et al. 2001), the most frequently encountered soil type in the area is *Lixisol* (tropical ferruginous soil), which is poorly to fully leached, overlying on sandy, clayey-sandy, and sandy-clayey materials.

The trials were set up to identify the nutrients limiting crop productivity with the ultimate ambition to be able to recommend site-specific sustainable land management options. In this chapter we focused on the response of maize crop to nutrients as NPK at 200 kg ha^{-1} which is the recommended fertilizer dose by the extension services containing 28 kg N ha^{-1}, 20 kg ha^{-1} P_2O_5 ha^{-1}, and 13 kg K ha^{-1}. The fertilizer was applied in broadcast during sowing. Two seeds per hole were sown to

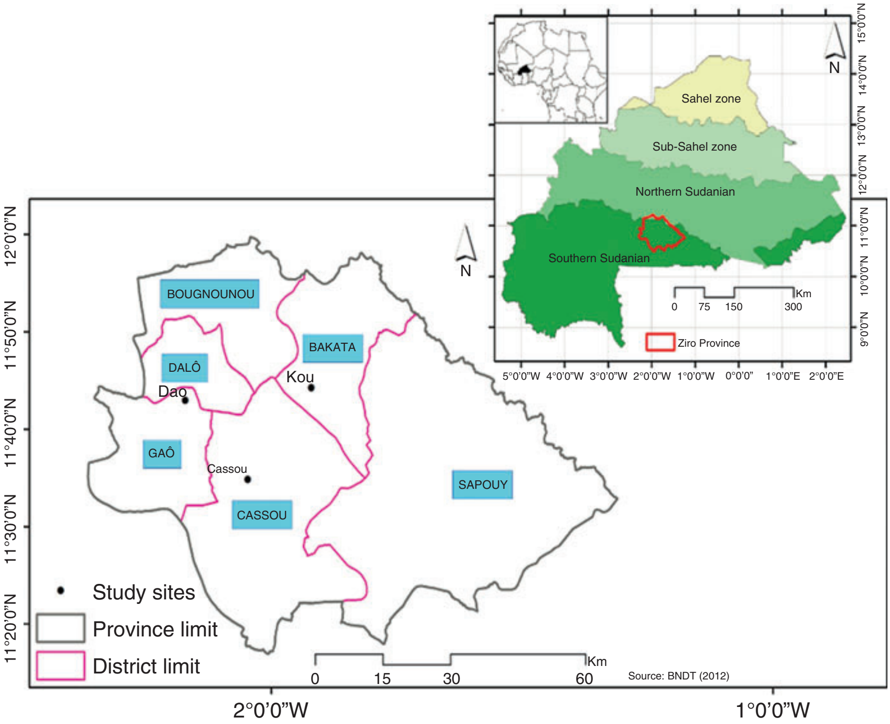


Fig. 1 Location of Ziro Province and study sites in Burkina Faso, West Africa

ensure germination and good stands of the crop and then thinned to one plant per hole, 5 days after emergence. The trial was carried out with an improved variety of medium maturing cycle maize named *Massongo*. Twelve experimental plots were established in Dao, Kou, and Cassou (Cassou 1, Cassou 2, Cassou 3, and Cassou 4), while data of Cassou 1 was used for calibration.

Each experimental plot covers an area of 100 m^{-2} (10 m × 10 m). Prior to trial establishment, initial soil status was characterized from composite sample (0–20 cm and 0–50 cm depths) analysis. Concentrations of total organic carbon and total nitrogen were determined using the Walkley-Black (1934) method and Kjeldahl method, respectively. The pH-H_2O measurements were made on a soil/water solution at a ratio of 1: 2.5. Available P was extracted according to the Bray I method. The cation exchange capacity (CEC) was obtained from Kjeldahl distillation. Information on soil textural properties were obtained from literature (BUNASOLS 2001).

In order to estimate maize crop yield and total aboveground biomass, hills were harvested within a sampling plot size of 50 m^2. On the harvested maize plants, grains and shoots were separated, oven-dried at 60 °C for 72 h, and weighted. The dry matter of stover weight (kg ha^{-1}) and the grain weight (kg ha^{-1}) was determined by scaling-up from the harvested plot area to 1 ha.

DSSAT Crop Growth Model

Crop Growth Model

CERES (Crop Environment Resource Synthesis)-Maize module within the DSSAT version 4.6 (Jones et al. 2003) was used. This model can be classified as a dynamic cropping system model with mechanistic and functional components. In the model, crop development is controlled by temperature, in terms of thermal degree days, while crop biomass formation depends on the simulation of LAI (leaf area index) and its direct relation to light interception. The model owns specificities when fine-tuning to simulate the phenological and physiological traits of specific crops including the processes of assimilation, respiration, crop development, and growth with regard to crop type. A set of reduction factors such as water, nitrogen, and phosphorus stresses influence the plant growth, senescence, and crop yield under unfavorable conditions.

Model Calibration and Validation Procedures

The DSSAT model was evaluated using data from 2014 to 2015 growing seasons at the site of Cassou 1. The model was calibrated for simulation of days after sowing to reach maturity for 100 days with respect to available information in the documentation for *Massongo* maize variety (Nitiema 2009). Then the adjustment of the other parameters consisted of making the best fit of the simulated outputs to the observed total aboveground biomass and grain yield within both growing seasons. The model was validated using site inputs and observation data from Dao, Cassou 2, Cassou 3, Cassou 4, and Kou sites. Farm operation dates and types that were implemented in all the sites and used as inputs in crop management file are described in Table 1.

Model Inputs

Soil Data

An accurate description of the soil profile is important for water-limiting simulations such as rainfed crops. The characteristics of the layers within the soil profile are integrated into the framework available within the crop models. They included limits of water content for each layer (lower limit, field capacity, etc.), pH-H_2O, organic matter, and nitrogen content (Table 2). From a depth of 50 cm to 120 cm, all soil parameters were set to the same value.

Climate File Inputs for Model Calibration and Validation

Weather data for running crop simulation models were obtained from the nearest weather station of Po. This includes daily rainfall and maximum and minimum air temperatures. Solar radiation was computed from Angstrom-type equation. The rainy period started in June and ended in October. The total precipitation for the year of experimentation was typical for the Sudanian regions of Central West Burkina Faso. The rainfall during the growing season was 638 mm and 670 mm in 2014 and 2015, respectively (Fig. 2). In DSSAT, FAO 56 method was chosen to estimate potential evapotranspiration.

Table 1 List of field operations used in the DSSAT model and derived for maize cropping for the two growing seasons in 2014 and 2015 in Ziro Province in Burkina Faso, West Africa. TBD is the total aboveground biomass, GY is the grain yield. Jul, July; Oct, October

Year	Treatment	Sowing date	Fertilizer application		Amount of N, P (kg ha^{-1})			Harvest date	Model outputs
			Type	Date 1	N	P	K		
2014	Control	10-Jul	–	–				31-Oct	TBD and GY at harvest
	+Fertilizer	10-Jul	NPK	10-Jul	28	20	13	31-Oct	TBD and GY at harvest
2015	Control	15-Jul	–	–				31-Oct	TBD and GY at harvest
	+Fertilizer	15-Jul	NPK	10-Jul	28	20	13	31-Oct	TBD and GY at harvest

Crop/Cultivar Input Files

Crop file was calibrated by varying the phenology parameters of the crop cultivars until the simulated phenology dates matched the observed dates. The focused dates were those associated with physiological maturity. After the phenology parameters were set, biomass assimilation and yield component coefficients were adjusted to represent as accurately as possible the measured biomass and yield. This includes the parameters in the cultivar (CUL) file such as P1 affecting anthesis day, PHINT value with leaf appearance rate and phyllochron interval, P2/P2R affecting photoperiod sensitivity, P5 affecting grain filling duration and yield components (G2: maximum possible number of kernels per plant; G3: kernel filling rate during the linear grain filling stage and under optimum conditions (mg day^{-1})) (Table 3).

Climate Projection Information

Post-processing of the raw regional climate model (RCM) (CLMcom and RCA4) data derived from 3 global climate models (GCM), (CNRM-CERFACS's CNRM-CM5 labeled CNRM, ICHEC-EC-Earth labeled ICHEC, MPI-M-MPI-ESM-LR labeled MPI) from the Coordinated Regional Downscaling Experiment (CORDEX) (Giorgi et al. 2009) was applied to the precipitation and temperature data. The precipitation data were bias-corrected at the Rossby Centre, SMHI, in Sweden using the distribution-based scaling method (DBS, Yang et al. 2010) and WATCH-Forcing-Data-ERA-Interim (WFDEI, Weedon et al. 2014) as reference dataset. WFDEI is a meteorological forcing dataset covering the period 1979–2014. Minimum and maximum temperatures were statically bias-corrected using baseline data from 2006 to 2015. For the provided climate data, two scenarios were used: RCP

Table 2 Soil profile horizon for DSSAT model calibration and validation of data from Cassou, Dao, and Kou villages in Burkina Faso, West Africa

Sites	Soil depth (cm)	Sand content %	Silt content %	Field capacity	Wilting point	Organic carbon %	Nitrogen %	Available phosphorus	pH-H_2O
Calibration									
Cassou 1	0–20	68	7	7	2	1.11	0.08	21.30	6.5
	0–50	54	7	7	2	1.04	0.07	10.64	6.5
Validation									
Dao	0–20	68	7	7	2	0.68	0.05	7.10	5.8
	0–50	54	23	19	13	0.66	0.05	6.87	5.8
Cassou 2	0–20	68	7	7	2	1.42	0.10	7.87	6.3
	0–50	54	23	19	13	1.22	0.09	7.21	6.3
Cassou 3	0–20	68	7	7	2	1.11	0.08	7.43	5.8
	0–50	54	23	19	13	1.07	0.08	7.76	5.4
Cassou 4	0–20	68	7	7	2	1.31	0.08	8.10	5.7
	0–50	54	23	19	13	1.31	0.08	7.30	5.9
Kou	0–20	68	7	7	2	0.67	0.05	6.32	6.3
	0–50	54	23	19	13	0.67	0.04	5.99	6.2
All sites	50–120	60	10	19	13	0.04	0.04	0.30	3.6

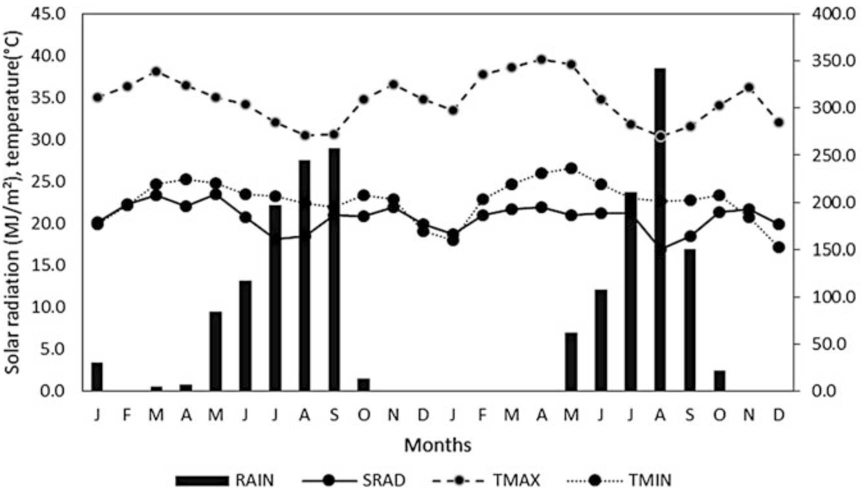


Fig. 2 Monthly rainfall, minimum and maximum temperatures, solar radiation (SRAD) distribution in 2014 and 2015 in the study sites (Cassou, Dao, and Kou) in Burkina Faso, West Africa

Table 3 Values of *Massongo* maize cultivar parameters as calibrated in the CERES-Maize crop model of DSSAT for the maize experiment in Ziro Province, Burkina Faso

P1 (°C day)	P2 (°C days)	P5 (°C days)	G2 (number)	G3 (mg day^{-1})	PHINT (°C day)
260	0.750	800	750	5.30	49

P1: Thermal time from seedling emergence to the end of the juvenile phase (expressed in °C day, above a base temperature of 8 °C) during which the plant is not responsive to changes in photoperiod. P2: Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 h). P5: Thermal time from silking to physiological maturity (expressed in °C day above a base temperature of 8 °C). G2: Maximum possible number of kernels per plant. G3: Kernel filling rate during the linear grain filling stage and under optimum conditions (mg day^{-1}). PHINT: Phyllochron interval, i.e., the interval in thermal time (°C day) between successive leaf tip appearances

(Representative Concentration Pathway) 4.5, the mitigation scenario where the global greenhouse gas emissions culminate in year 2040 and then decrease, and the RCP8.5, the "business-as-usual" scenario where the emissions continue to accelerate. Historical scenario concerns the observed 30-year period data from 1981 to 2010 at Po station.

Model Evaluation and Statistical Analysis

In the model calibration, the observed and simulated means were compared using two-sample t-test for paired data in R software across the treatments and season during the 2 years (2014–2015) of the experiments. Statistics used for the performance evaluation of DSSAT model were the root-mean-square error (RMSE) (Eq. 1) and the coefficient of determination (R^2) which were calculated from observed and simulated variables. The value of RMSE equal to zero indicated the goodness of fit between predicted and observed data and evaluated model performance and accuracy in prediction. The coefficient of determination's value close to 1 indicates better prediction, while R^2 value of zero indicates no predictability.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \tag{1}$$

The root-mean-square error (RMSE), observation (O), simulations (S)

Scenario Analysis

With the seasonal analysis tool of DSSAT, predictions of grain yield over the climate scenario periods were done. Yield frequency plots with the cumulative probability distribution (CPD) for the base period (1981–2010) as historical and near future period (2021–2050) were developed. This allowed the visualization of trends and effects of climate change scenarios and resilience attributes of recommended fertilizer inputs (yield stability and ranges). In CPD, the basic idea is to look at mean yield and variance at 0.5 cumulative probabilities. For a given minimum yield level, the risk of each treatment was defined by looking at the cumulative probability of obtaining such a yield level (Ngwira et al. 2014).

Results and Discussion

Model Calibration and Evaluation for Maize Cultivar *Massongo*

The crop production variables used for the study were maturity date, total aboveground biomass, and maize grain yield based on six genetic coefficients of cultivar *Massongo* of maize, which were estimated in the present study (Table 2). The range of those coefficients lies within the values reported by other researchers for medium maturing maize varieties in Africa (Ngwira et al. 2014).

The calibration process revealed that simulated total aboveground biomass gave 1335 kg ha^{-1} greater yield than observed although the averaged biomass showed no significant ($p > 0.05$) differences between observation and simulation (Table 4). Observed grain yields displayed higher standard deviation compared to simulated ones. Also, the simulation overpredicted the mean yields as a result of general overprediction in both rainfall seasons and soil fertility options (Table 4). Overall, comparison between observed and simulated yields using two-sample t-test for unpaired data showed that the mean values were not statistically different

Table 4 Observed and simulated maize *Massongo* total aboveground biomass (TAB) and grain yields (GY) in 2014 and 2015

Crop parameters	Observed yields (kg ha^{-1})		Simulated yields (kg ha^{-1})		Two-sample t-test for paired data	R^2	RMSE (kg ha^{-1})
n = 4	Mean	std	Mean	std			
TAB	6738	3498	7706	559	NS	0.87	2186
GY	750	575	990	206	NS	0.74	617

n, number of plots; std, standard deviation; NS, not significant at the 0.05 level

($p > 0.05$) as indicated in Table 3. This shows that the model was successfully calibrated for the cultivar *Massango* as well as for the two treatments and two seasons of study. Moreover, in the years of calibration, DSSAT was able to capture the relative decrease in grain yield between the recommended and non-fertilizer treatments, thus generating the best level of accuracy with its high R^2 (0.74) which is specifically used to assess the extent to which magnitudes of observed means are related to the simulated ones, and allows for sensitivity toward differences between them as well as the proportionality changes.

The CERES-Maize model was evaluated by comparing simulated and observed yield data for sites of Cassou 2, Cassou 3, Cassou 4, Dao, and Kou for 2014 and 2015 growing seasons that are considered to be an independent dataset to Cassou 1. Although, the evaluation experiments were conducted at the different sites, the management operations and in particular the fertilizer inputs were the same as on the calibration site (Table 1). However, soil and climate conditions were different (Table 2, Fig. 2). Validation of DSSAT model for yield simulation was challenging because the stable percentage of organic matter factor, which is one of the soil parameters that had significant effect on yield, should be adjusted. Unique value of stable organic matter at 0–20 cm that provided simulated yields comparable to observed yields was 20%.

Graphically and in overall, regression plot shows that simulated aboveground biomass was well represented in comparison with the observations using the modified parameters for all the experiments (Fig. 3). The model simulated maize grain over all treatments with difference of 9% for total aboveground biomass and grain yield. Ngwira et al. (2014) and Bakhsh et al. (2013) estimated that the error in predicting yield for all treatments was below 12% which was considered to be "good." Overall, the RMSE was found to be 2010 kg ha^{-1} and 643 kg ha^{-1} for total aboveground biomass and grain yield, respectively. In the present study, the DSSAT simulations were of good quality for the mean grain yield and mean aboveground biomass across the two seasons and four sites; such conclusion is based on moderate parameterization efforts and statistics for on-farm growing conditions. It can be outlined that the model has been shown to simulate maize growth under strongly contrasting environmental conditions in the tropics, while it has functions that describe the changes in system states in response to external drivers (e.g., weather and management practices).

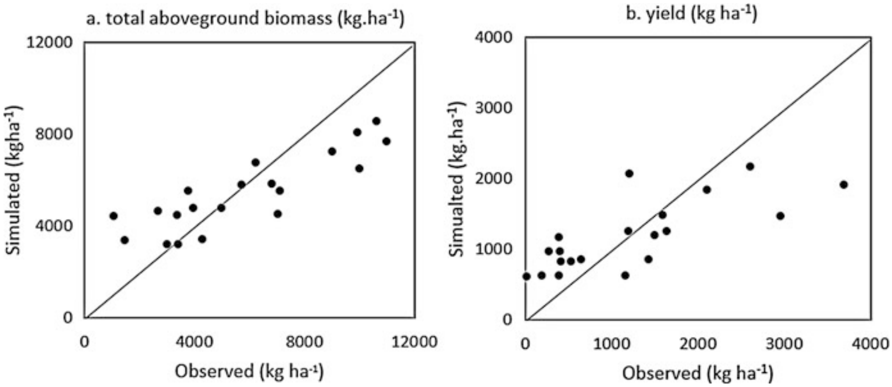


Fig. 3 Regression of simulation for measured maize *Massongo* total aboveground biomass (**a**) and grain yields (**b**) (kg ha^{-1}) after model validation

Table 5 Model validation, observed and simulated maize *Massongo* total aboveground biomass (TAB), and grain yields (GY) between 2014 and 2015 in five study sites (Cassou 2, Cassou 3, Cassou 4, Dao, Kou) in Burkina Faso, West Africa

n = 10	Observed yields (kg ha^{-1})	Simulated yields (kg ha^{-1})	Two-sample t-test for paired data	R^2	RMSE (kg ha^{-1})
TAB-Control	4879.3	4836.4	NS	0.66	3019
TAB-NPK	6682.4	5959.2	NS	0.75	3154
GY-Control	1104.5	1076.5	S	0.34	1054
GY-NPK	1324.0	1297.9	NS	0.76	1057

NS, no significant difference at the 0.05 level; S, significant difference at the 0.05 level

However, the variation between the individual plots was quite high, resulting in an R^2-value of 0.74 showing that at field level and for total aboveground biomass, the mean overall treatment value was a good predictor, whereas the individual plot-wise yield predictions may be more uncertain. Indeed, in Table 5 it is shown that the model simulates grain yield and total aboveground biomass with higher reliability for fertilized plots than non-fertilized plots where R^2 was below 0.5. Some errors related to the gap between the simulated and observed value are mainly due to the level of variability between plots. An experiment under on-farm conditions with various treatments over several cropping seasons may be enough complex for crop production estimation because of the involvement of several factors like pests; heterogeneity within the crop management intensity, e.g., plant density; various interacting nutrient stresses such as micronutrients (Folberth et al. 2014; Voortman et al. 2003); and the soil physical discontinuities with the consequence of a huge yield gap. For the sites in Africa, recorded yield reached only 20% of the attainable yield confirming the large yield gap which weakens the use of favorable seasonal weather conditions (Hoffmann et al. 2017). Nevertheless, the evaluation of the simulation model is on a good level being used as a decision support tool to evaluate the impact of usual fertilizer input rates on farmers' fields.

Interannual and Seasonal Variability in Rainfall for Projected Climate Scenarios

With reference to the analysis of future climatic change as projected by regional climate models around the 2030s (2021–2050), mean rainfall in the maize growing season is predicted to decrease slightly in the Sudanian Savanna environments of Central West Burkina Faso for all the climate scenarios as compared to the simulated value for the historical scenario (1980–2010) except for ICHEC under RCP8.5 (Fig. 4a). Specifically, three regional climate change projections for Central West Burkina Faso indicate a decrease in rainfall during the growing period of maize to the tune of 3–9% in 2030s under RCP4.5. ICHEC predicted an increase of rainfall of 25% under RCP8.5. Similar small magnitude of variation in RCP4.5 and higher magnitude of variation in RCP8.5 were also obtained for mean annual rainfall which is predicted to increase in the Sudanian Savanna by about 1.7% and 1.9% in 2030s and by 4.4% and 16.1% in 2030s under the respective scenarios RCP4.5 and RCP8.5 (Mohammed et al. 2016). With reference to CMIP5 (Coupled Model Intercomparison Project Phase 5), the majority of the climate model outputs we used seem to be contrary to the positive precipitation trend which is predicted by 50% of the models in CMIP5 model ensemble. The results of our climate models are probably closer to the 25% of the models in the CMIP5 archive showing robust decreasing precipitation trend although only one of our scenarios was in agreement with these previous studies (Sultan and Gaetani 2016). In Fig. 4a, b, higher warming is expected for all climate scenarios with RCP8.5 and CNRM 8.5 at the highest.

For analysis of intra-seasonal rainfall distribution, the monthly rainfall variability across the years within the growing season is shown in Fig. 5. Across the months, more consistent trends of rainfall in the growing period among the climate scenarios were obtained under RCP4.5 than under RCP8.5. There will be significant reduction in the distribution of rainfall at the end of the growing season (October) especially in the output of the MPI climate model with RCP4.5 and RCP8.5 (Fig. 5d). Although our study is in disagreement with Ngwira et al. (2014) who used RegCM4 in Malawi projecting more rainfall at planting than in the historical weather data, our conclusions confirm the findings of these authors that there will be a reduction in the length of the growing season in the future. In RCP4.5, lower variance of rainfall across July adding to the lower water volume in this month is in contrast with Tachie-Obeng et al. (2013) who reported from projections an increase in rainfall at the onset of the wet season in Northern Ghana, with a decline in mid-season rainfall in June, followed by a significant shift in the distribution of rainfall toward the tail end of the season, especially in November. In our case and for RCP8.5, the increase in

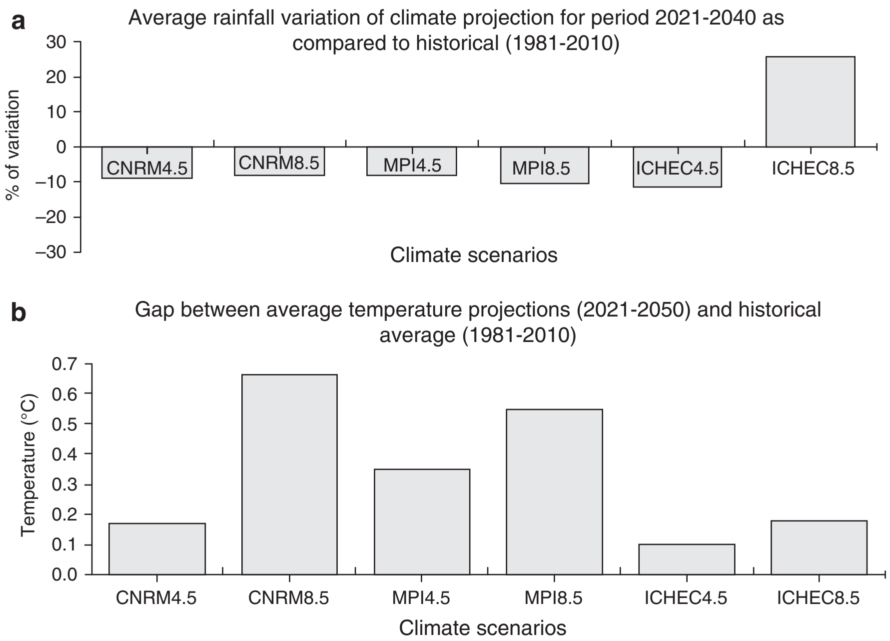


Fig. 4 Comparison of rainfall during the growing period of maize in the baseline (1981–2010) and future climate periods (2021–2050) under RCP4.5 and RCP8.5 climate scenarios for the study sites (Cassou, Dao, and Kou) in Burkina Faso, West Africa. (**a**) Percentage change in rainfall during the growing period in climate projections as compared with historical data average; (**b**) gap between average temperature projections and historical average temperature during the growing season

rainfall in the future in the middle season seems to be in favor and in benefit of the normal crop growth and development as this period corresponds to critical stages of maize growth, i.e., flowering and grain filling.

In summary, the use of multiple RCM models that was expected to reduce uncertainty in the model projections seems to show disparities in the climate warming particularly for maximum temperature, while the precipitation projections for only one model (ICHEC) out of the three show an increasing trend. Future rainfall distribution seems to be favorable over the growing season of maize.

Risk Analysis

The seasonal analysis program of DSSAT 4.6 was used to compare two management options with recommended fertilizer inputs (Fig. 7) and no fertilizer (Fig. 6) in a soil with medium soil fertility status represented by the soil at Cassou 3 (Table 2). The simulations were carried out for a 30-year period with daily climate data consisting of rainfall derived from three climate models under RCP4.5 and RCP8.5 scenarios and from the historical time series. About 960 runs were derived from the set of

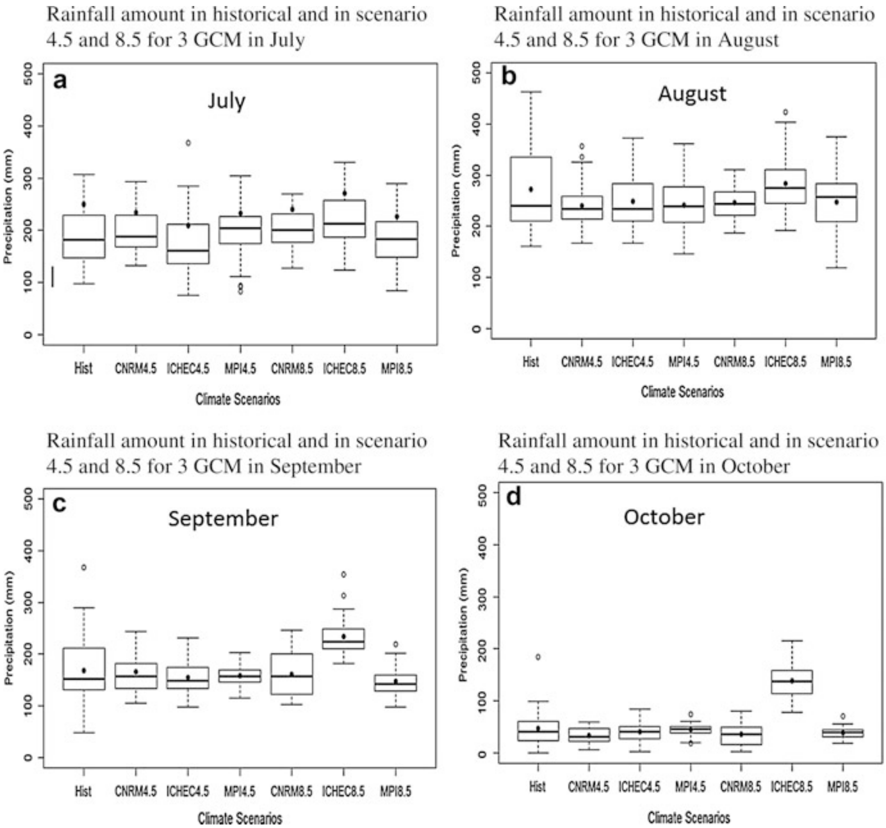


Fig. 5 Seasonal variability of growing period rainfall under different scenarios over the simulation period (30 years) in both RCP4.5 and RCP8.5. Each box in the graph shows the distribution of rainfall over the simulation period. The boundary of the box closest to zero indicates the 25th percentile, the broken line within the box marks the mean, the solid one marks the median, and the upper boundary of the box indicates the 75th percentile. Whiskers above and below the box indicate the 95th and 5th percentiles. Black spot represents the mean. CNRM refers to rainfall amount under climate scenarios using CNRM-CERFACS-CNRM-CM5 global climate model; ICHEC refers to rainfall amount under climate scenarios using ICHEC-EC-Earth global climate model; and MPI refers to MPI-M-MPI-ESM-LR global climate outputs. (**a**) Rainfall amount in historical and in scenario 4.5 and 8.5 for 3 GCM in July. (**b**) Rainfall amount in historical and in scenario 4.5 and 8.5 for 3 GCM in August. (**c**) Rainfall amount in historical and in scenario 4.5 and 8.5 for 3 GCM in September. (**d**) Rainfall amount in historical and in scenario 4.5 and 8.5 for 3 GCM in October

treatments of fertilizer inputs tested and encompassed variable rainfall profiles (dry, normal, and wet seasons) while allowing to explore and to generate potential impact of climate seasonality on the risk in the cropping systems.

Figure 6 shows yield changes over 30 years and 3GCMs for RCP4.5 and RCP8.5 when no fertilizer was applied on a soil with moderate fertility status. Under RCP4.5, the plots of cumulative probability distribution (CPD) at the level of 0.5 showed that

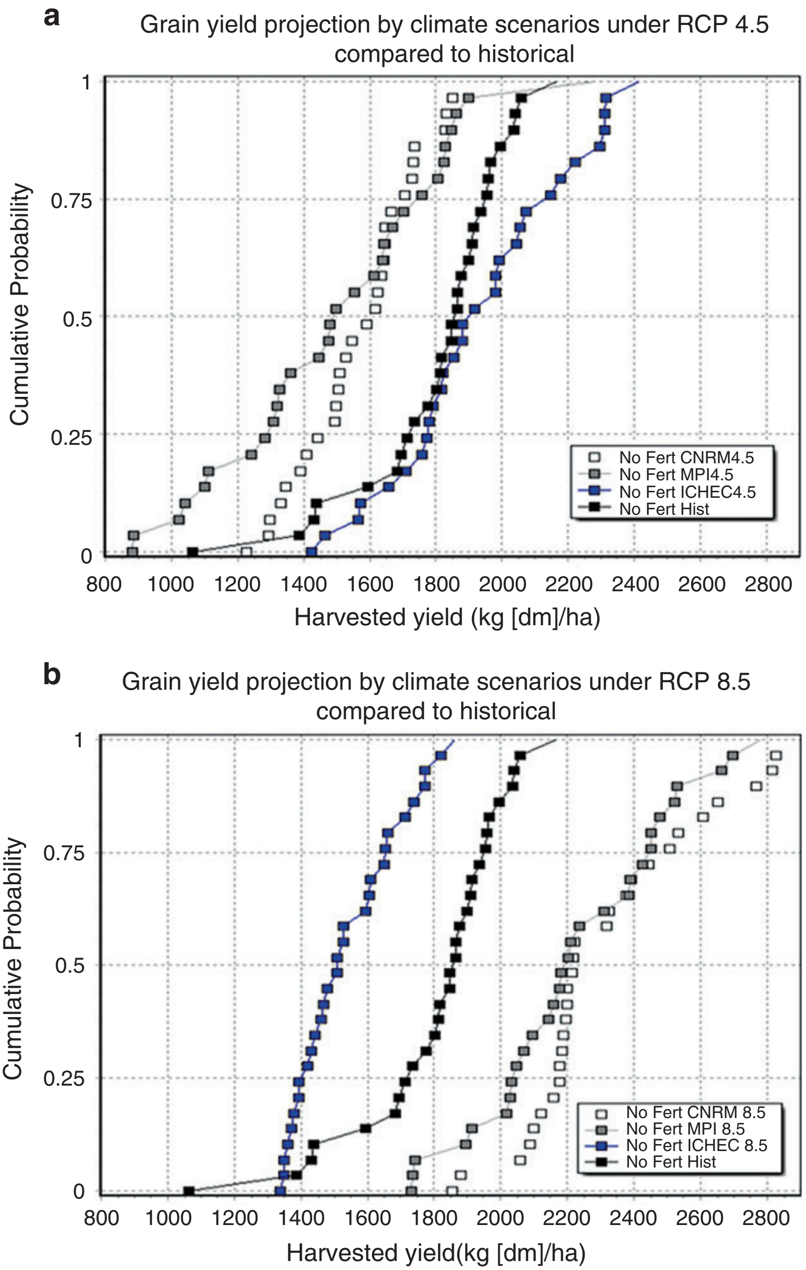


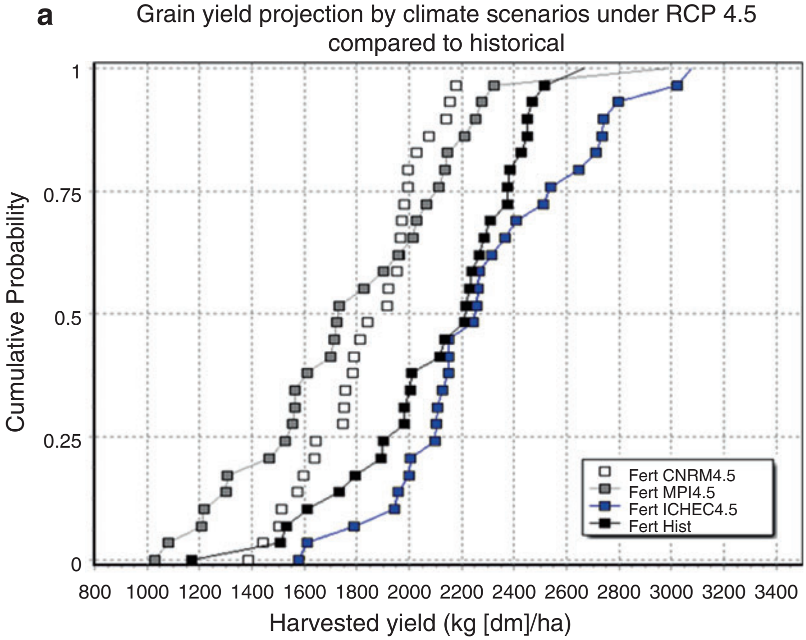
Fig. 6 Cumulative probability distribution plots of maize yields for no fertilizer treatment under medium soil fertility (Cassou3) with the historical baseline (1981–2010), and 2030s time periods under RCP4.5 and RCP8.5 climate scenario with 3 GCM. No fert Hist is the treatment without fertilizer under historical climate. No fert CNRM 4.5 and CNRM 8.5 are treatment without fertilizer under RCP4.5 and RCP8.5, respectively, for regional climate CNRM-CERFACS-CNRM-CM5.

the lowest mean yield was predicted under CNRM and MPI climate scenarios, while the highest yields were both with historical and ICHEC climate scenarios (Fig. 6a). This pattern was strongly contrasting for the predicted yield with RCP8.5 (Fig. 6b). In RCP8.5, yield will be negatively affected by higher amounts of rainfall in the ICHEC climate scenario as compared with historical yield. Similarly responses of maize yields to the outputs of nine GCMs without adaptation options showed general tendency toward diminishing future maize yields in the single cropping season of the savanna zone, ranging from −6.3% to −42.6% in the near future (Tachie-Obeng et al. 2013). Meanwhile, in our results for RCP8.5, mean-variance of yield and distribution of yield along with maximum and minimum values were higher for the two other climate scenarios (CNRM and MPI) than for historical climate scenario.

Figure 7 shows yield changes over 30 years for historical and 3GCMs in RCP4.5 and RCP8.5 when applying the recommended fertilizer rates. Under RCP8.5, future average yields (at CDP = 0.5) were projected to increase by 13% (for both CNRM and MPI) during the near future compared with historical climate, whereas there was an 18% decline in maize yield in the ICHIEC scenario when compared with the historical scenario. Under RCP4.5, the decline in simulated yield was also observed for the other climate model scenarios but less pronounced.

Comparing the two RCP scenarios, the results in Figs. 6 and 7 revealed that globally maize grown under nutrient stress conditions (moderate soil fertility and without fertilizer) has favorable conditions under RCP4.5 for the ICHEC scenario, but not for the MPI and CNRM scenarios, whereas under RCP8.5, the conditions are more favorable for the MPI and CNRM scenarios. The inconsistency in the outcomes is similar to the findings by Araya et al. (2015) who found out that there will be an increase and decrease in the yield of chickpea varieties in central highlands of Ethiopia in the upcoming periods depending on the projected climate change under both RCPs by 2050s. Nevertheless, the projections of maize yields confer the same trend for both treatments (without fertilizer and with fertilizer) in response to climate change projections in each of the RCPs. The results contrast with findings from Waongo et al. (2015) who reported that with 8 RCMs and a regional crop model, irrespective of the RCP and period, a higher positive change (>40%) of maize mean yield is expected in the Central West Burkina Faso. In our study, the main contrast exists between RCP4.5 and RCP8.5, where only the ICHEC scenario does not benefit the maize crop under RCP8.5 by resulting in reduced yield within the range of the simulations (yield between 0% and 100% of CDP lower than historic) although its projection of rainfall amount was the highest with this scenario (Figs. 4 and 5). Maize grown under nutrient stress condition (moderate soil fertility without fertilizer) may suffer from the potential nutrient depletion of arable land

Fig. 6 (continued) No fert MPI 4.5 and MPI 8.5 are treatment without fertilizer under RCP4.5 and RCP8.5, respectively, for regional climate MPI-M-MPI-ESM-LR. No Fert ICHEC4.5 and ICHEC8.5 are treatment without fertilizer under RCP4.5 and RCP8.5, respectively, for regional climate ICHEC-EC-Earth



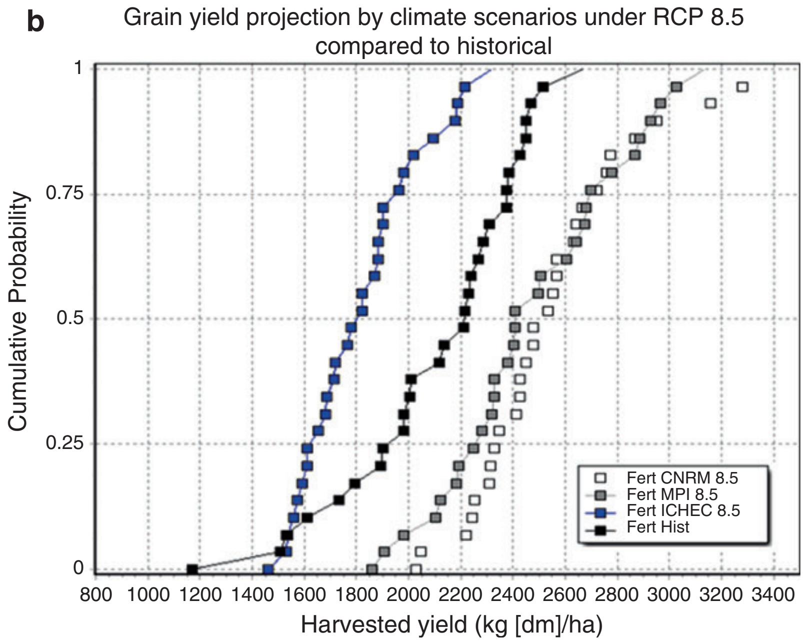


Fig. 7 Cumulative probability distribution plots of maize yields for fertilized treatment under medium soil fertility (Cassou3) with the historical baseline (1981–2010) and 2030s time periods under RCP4.5 and RCP8.5 climate scenarios with 3 GCM. Fert Hist is the treatment with fertilizer under historical climate. Fert CNRM 4.5 and CNRM 8.5 are treatment with fertilizer under RCP4.5 and RCP8.5, respectively, for regional climate CNRM-CERFACS-CNRM-CM5. Fert MPI 4.5 and

including micronutrients due to nutrient leaching. Water erosion is also higher as a result of intense rainfall events (Folberth et al. 2012) which have been shown to lead to significant mining of soil nitrogen reserves. Effective conclusions can be drawn up after making more complex analysis from climate change scenarios while taking into account important climatic parameters such as elevated temperatures as they might shorten the growth duration and be a stress factor. Under low nutrient stress (with fertilizer application), maize yields are slightly higher (approx. 200 kg ha^{-1}) irrespective of the climate model and RCP scenarios.

Our study confirms that modifying the fertilizer rate according to seasonal weather forecasting could help better realize the potential for intensification. However the validity of our findings may suffer from the lack of cumulative benefits of crop rotation systems, thereby underestimating maize grain yield as the DSSAT model uses the same initial soil conditions for the entire simulation period. Hence refinements of the algorithms to simulate changes in soil properties in DSSAT are recommended in order to sufficiently and accurately predict yield of crop rotation systems in the seasonal analysis module (Ngwira et al. 2014). As rainfall appeared to consistently meet crop water demand, our study is likely to support the conclusion by Araya et al. (2015) that there was no substantial difference in yield across the future scenarios. The study may be extended to assess the compensation by effects of increased CO_2. Nevertheless, at the current status of knowledge, evidence was made that the positive CO_2 effect is less significant on C_4 crop (e.g., maize, millet, sorghum) for the region (Roudier et al. 2011).

Policy-Induced Recommendations

Given a population growth rate of 2.9% per annum in 2015 and taking into account a maize yield target of 4000 kg ha^{-1} calculated to satisfy a healthy diet of an average smallholder family of 5.4 members (Ngwira et al. 2014), none of the scenarios even with recommended fertilizer rate has reached these yield levels within the limits of the CPD (Figs. 6 and 7). Indeed our climate change impact assessment shows that if current and historical levels of grain yield do not meet the demand, any further reduction in yield, as indicated by the predicted yield losses even with recommended fertilizer rates, will entail some risks of leaching for farmers. The model also highlighted the influence of inorganic fertilizer on increasing the average maize yields on a moderately fertile soil irrespective of the climate model and RCP. Based on these findings, policy direction and support for potential measures to increase

Fig. 7 (continued) MPI 8.5 are treatment with fertilizer under RCP4.5 and RCP8.5, respectively, for regional climate MPI-M-MPI-ESM-LR. Fert ICHEC4.5 and ICHEC8.5 are treatment with fertilizer under RCP4.5 and RCP8.5, respectively, for regional climate ICHEC-EC-Earth maize yield can be reinforced with integrated soil fertility management (combination of mineral fertilizer and crop rotations with legumes, splitting of N fertilizer applications to avoid excessive leaching, low-release N fertilizers) and soil conservation with inputs from agroforestry and water and soil conservation practices that would preserve natural resources while increasing yields.

Conclusions

DSSAT model parameterized with site-specific inputs allows evaluating the impacts of projected rainfall variability and temperature on maize production using information from regional downscaling and bias correction of the output of 3 GCMs and the interaction with recommended fertilizer application rates. Total aboveground biomass and grain yield were calibrated and validated with a dataset derived from contrasting sites in Central West Burkina Faso with two soil fertility management options: recommended fertilizer dose and no fertilizer. Overall acceptable $R^2 > 0.5$ and RMSE values were obtained from those exercises. With the validated DSSAT model, the risks associated with future climate change scenarios from 3 GCMs were assessed as well as the effectiveness of fertilizing options to mitigate the effects of rainfall variability on maize yield in the near future under 2 RCPs (4.5 and 8.5). Both non-fertilized and recommended fertilizer treatments responded similarly to the impacts of future climate change, but projections under RCP4.5 contrast to the ones under RCP8.5, and there are also inconsistencies depending on the GCMs. Under RCP8.5, two out of three GCMs showed that maize yield under future climate may increase slightly compared to historical conditions by an average of 17%. However, in RCP8.5, when DSSAT is run with the output of the ICHEC-EC-Earth model, grain yield is projected to decrease by a maximum of 16%, whereas under RCP4.5, maize yield slightly increased by less than 5%. As there is no overall trend of gain or loss in maize yield in the different scenarios (currently taking into account only future changes in rainfall and temperature), there is a need to add the CO_2 effect in future climate impact studies in Burkina Faso.

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