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Adaptation to climate change: The impacts of optimized planting dates on attainable maize yields under rainfed conditions in Burkina Faso

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ABSTRACT

The high intra-seasonal rainfall variability and the lack of adaptive capacities are the major limiting factors for rainfed agricultural production in smallholder farming systems across Sub-Saharan Africa. Therefore, the crop planting date, a low-cost agricultural management strategy aiming to alleviate crop water stress can contribute to enhance agricultural decision-making, particularly as a climate change adaptation strategy. By considering the crop water requirements throughout the crop growing cycle using a process-based crop model in conjunction with a fuzzy rule-based planting date approach, location-specific planting rules were derived for maize cropping in Burkina Faso (BF). Then, they were applied to regional future climate projections to derive optimized planting dates (OPDs) for the 2020s (2011–2030) and the 2040s (2031–2050), respectively. Based on potential maize yield simulations driven by climate change projections and planting dates, the OPD approach was compared with a well-established planting date method for West Africa and evaluated as a potential adaptation strategy for climate change. On average, the OPD approach achieved approximately +15% higher potential maize yield regardless of the regional climate model (RCM) and the period. However, the potential yield surpluses strongly decreased from the North to the South. Regarding climate change adaptation, the combined impact of climate change and the OPD approach has shown on average, a mean maize yield deviation between −23% and 34% in comparison to the 1989–2008 baseline period. Yield deviation is found to depend strongly on the RCM and location. The RCM ensemble mean yield for the period 2011–2050 revealed a maximum decrease of 8% compared to the baseline period. On the one hand, these findings highlight the potential of the OPDs as a crop management strategy but, on the other hand, it is apparent that farmers need to combine the OPDs with others suited farming practices to adequately respond to climate change.

1. Introduction

The literature abounds with evidences that global climate change is expected to have negative impacts on socio-economical sectors, particularly in agriculture (e.g. Darwin et al., 1995; Rosenzweig and Hillel, 1998; Thomas et al., 2004; Risbey, 2008; Müller et al., 2011; Aaheim et al., 2012; Gosling, 2013). The impact of climate change on agricultural productivity is not expected to be geographically uniform. In the tropical regions, rising temperatures and changes in rainfall patterns, including increased seasonal and interannual rainfall variability, can directly cause yield reduction for most of the food crops and, therefore, reduce food production (Nelson et al., 2009; IPCC, 2014). Sub-Saharan Africa (SSA) is one of the most vulnerable regions to climate change since agriculture is heavily dominated by rainfed agriculture. Moreover, rainfed agriculture in SSA is dominated by a smallholder farming system with limited options for investment (i.e. fertilizers, pesticides, machines) and irrigation, thereby the most vulnerable agricultural system (Roudier et al., 2011; Calzadilla et al., 2013). Nonetheless, with low yield, rainfed agriculture is the main occupation and source of income for the majority of SSA population and, therefore, has a great influence on regional food security (Ringler et al., 2010; Webber et al., 2014). Amongst others, crop production changes are mainly driven by both precipitation and temperature changes (Wallach et al., 2006). Consequently, climate change will pose huge challenges to food security.

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Climate change without adaptation is projected to strongly impact on crop productivity. Indeed, temperature increases of 2 °C or more above late-20th century levels is expected to negatively affect the major crops (i.e. wheat, rice, and maize) in temperate and tropical regions, although for individual locations the signal is of medium confidence (IPCC, 2014). For temperature, Lobell et al. (2011) found that each degree-day above 30 °C reduces crop yield by 1% under optimal rainfed conditions and by 1.7% under drought conditions in Africa. On average, climate change is expected to decrease crop yields by 18% and 22% by mid-21st century in Southern Africa and across SSA, respectively (IPCC, 2014). Simulations based on a warmer climate change scenario have shown that maize yield is expected to be decreased by more than 5% for 2050 in East Africa, particularly in the northernmost regions (Thornton et al., 2010). In addition, a meta-analysis of 16 studies over West Africa by Roudier et al. (2011) has highlighted that overall climate scenarios and models, countries and crops, projected impacts are in general slightly negative (−10%). Likewise, from a systematic review and meta-analysis of 52 publications, Knox et al. (2012) found that projected mean change in yield of −5% (maize), −15% (sorghum) and −10% (millet) are expected by 2050 across Africa. Faced with the underlying threats and challenges, management decisions regarding cultural practices and inputs will play a crucial role in the enhancement of crop production in SSA (Lobell et al., 2008; Tingem et al., 2009)

Technologies or approaches that have the potential to support farmers in the fields of soil conservation and water management are likely to make a difference for food security and agricultural development in SSA. However, since farmers' options for coping and adaptation are particularly limited in that region (Antwi-Agyei et al., 2013), it is necessary to carefully select crop management strategies that account for capacity constraints and therefore, can efficiently help farmers adapting to climate change. Many studies have stressed farmers' coping and adaptation strategies in SSA (e.g. Roncoli et al., 2001; Kaboré and Reij, 2004; Barbier et al., 2009; Zampaligré et al., 2014; Webber et al., 2014). Among the broad range of crop management strategies, strategies fitting in the pool of low-cost strategies have been adopted by farmers. Thus, low-cost strategies such as stone bunds, micro-water harvesting (*Zaï*) and water harvesting (*Demi-Lune*) have been largely adopted by farmers (Kaboré and Reij, 2004; Sawadogo, 2011). In fact, the high level of poverty in SSA leads farmers to abandon some crop management technologies and approaches, even though they are proven to be efficient. Thereby, only those strategies which require little resources in terms of labor and money have a chance to engage a large number of farmers. Given farmers' capacity constraints and the high variability of the onset of the rainy season in SSA, approaches to better estimate the onset of growing season for planting crops might be valuable options as crop management strategies.

Adapted crop planting date estimation is crucial for rainfed agriculture and a challenging task for scientists in SSA. Efforts have been made to estimate the suitable time for planting crops. Approaches which use crop-generic assumptions in combination with the onset of the rainy season are the most often used in SSA (e.g. Stern et al., 1981, 1982; Sivakumar, 1988; Dodd and Jolliffe, 2001; Diallo, 2001). They have the potential to alleviate crop failure caused by water stress during the juvenile stage of crop development. Although these approaches have proven to be useful in SSA (Sivakumar, 1992), they do not account for the risk of prolonged dry spells during the following crop development stages. For this reason, Laux et al. (2010) highlighted that crop planting date have to aim to minimize water stress during the entire growing period to significantly increase the crop production. Likewise, Waongo et al. (2014) stressed that optimized planting dates (OPDs) have the potential to improve crop production in SSA. The latter study demonstrated that the OPDs achieved higher potential yield for maize cropping in Burkina Faso. Besides, the OPDs have the potential to narrow interannual variability of maize yield. Moreover, this study highlighted that such management strategy which required no implementation costs from farmers might have the consent of farmers for uptake. However, present climate data are concerned in the aforementioned study and the performance of the OPDs in the context of climate change is still an open question. Apart from that, the simulation of the impacts of regional climate change using potential adaptation strategies can help support stakeholders for evaluating climate change adaptation options at finer spatial scale rather than global scale. Finer scale climate impact studies would, however, require regional climate data, which are commonly derived from RCMs and statistical methods.

Nested modeling (i.e. dynamic downscaling modeling) and empirical-statistical downscaling approaches are the most commonly used (Moriondo and Bindi, 2006; Jung and Kunstmann, 2007) to derive climate data at finer scale. The first approach used global circulation models (GCMs) outputs to provide boundary conditions for RCMs with higher spatial resolution (Giorgi and Mearns, 1999). The second approach combines assumptions and statistical techniques to downscale local and regional climate variables from GCM outputs (e.g. Bárdossy, 1997). Because of the crucial role of climate models in the process of decision-making, these two approaches are intensively used to derived regional climate change data which are subsequently used for regional climate change impact studies. For instance, the ongoing Coordinated Regional Climate Downscaling Experiment (CORDEX) is using the nested modeling approach in combination with the latest developed GHG emission scenarios, the Representative Concentration Pathways (RCPs) (Moss et al., 2008, 2010) to produce projected future climate data at regional scale for different regions worldwide. Thus, in light of the regional climate change simulations over Africa domain – CORDEX-Africa (e.g. Nikulin et al., 2012), further impact studies are necessary to explore combined effects of climate change and potential adaptation strategies in Africa.

By using regional climate change projections from CORDEX-Africa, the aim of this study is (1) to evaluate the comparative benefits of the OPD approach against a rainfall-based planting date approach in the context of climate change and (2) to assess the potential impact of regional climate change in combination with the OPDs on maize productivity. For this purpose, regional climate change data from eight RCMs and two RCPs are used to drive a crop model. First, RCM control runs (CTRL) are analyzed to have a comprehensive overview of the performance of RCMs for the study area. Second, potential maize yield is simulated using the General Large Area Model for annual crops, GLAM (Challinor et al., 2004) and RCM outputs for the GHG emission scenarios RCP4.5 and RCP8.5 (Detlef et al., 2009). Planting date computation approaches of Diallo (2001) and Waongo et al. (2014) are used as crop management strategies in the process of crop yield simulation. Then, based on the two planting date strategies, a comparative analysis of the simulated crop yield is performed and the OPD approach is evaluated as climate change adaptation strategy.

2. Study area

Burkina Faso (BF) is a West African country located in the midwest SSA region. It covers an area of about 274,200 km^2 and lies between 9 and 15.5° N and between 6° W and 3° E. The country is mainly flat, with a mean altitude of about 300 m a.s.l. (Azoumah et al., 2010). Its climate is characterized by two distinct seasons: a rainy season and a dry season. Rainfall distribution across the country follows predominantly a southward gradient: mean annual precipitation decreases from more than 1100 mm in the South to

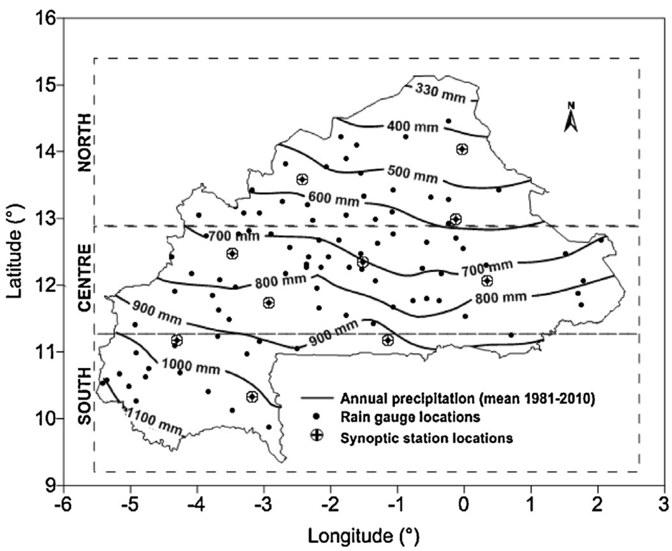

Fig. 1. Mean annual precipitation (30-yr mean isohyets). Precipitation interpolation has been performed using an ordinary kriging (OK) method. The dotted boxes represent roughly the three agroecological zones (North, Centre, South) across BF.

around 300 mm in the North (Fig. 1). The daily mean temperature varies between 17 and 37 °C (21 and 34 °C) during the dry season (rainy season) across BF (Sivakumar and Gnoumou, 1987).

Agricultural activities mainly take place during the rainy season from May to October with varying growing season of three to six months from the North to the South (Sivakumar and Gnoumou, 1987). BF's economy relies strongly on agricultural products and about 80% of the population is involved in agriculture (Brooks et al., 2013). In addition, agricultural production contributes more than 30% to the GDP and is the main source of income for the rural population (Diao et al., 2007). Cereal crop production is predominantly subsistence-oriented. Sorghum (*Sorghum bicolor*), millet (*Panicum sp.*) and maize (*Zea mays* L.) are the main pillars of Burkina Faso's food security. The annual production of these three staple crops has shown a rapid increase since 1984 with highest increase rate for maize. Since 2000, maize is ranked as the second cereal crop after sorghum in terms of annual production (Fig. 2).

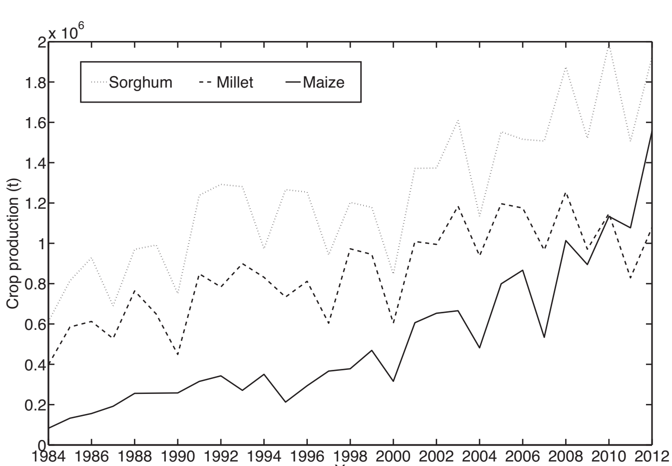

Fig. 2. Evolution of annual crop production for three staple crops in Burkina Faso. Data have been retrieved from CountrySTAT, FAO database (https://countrystat.org/home.aspx?c=BFA).

Table 1
RCMs and institution names and the corresponding labels used in this study.

RCM (GCM)	GCM's institution name (country)	Label
RCA4 (CanESM2)	CCCma (Canada)	CCCma
RCA4 (CNRM-CM5)	CNRM-CERFACS (France)	CNRM
RCA4 (EC-EARTH)	ICHEC (Europe)	ICHEC
RCA4 (MIROC5)	MIROC (Japan)	MIROC
RCA4 (HadGEM2-ES)	MOHC (UK)	MOHC
RCA4 (MPI-ESM-LR)	MPI-M (Germany)	MPI
RCA4 (NorESM1-M)	NCC (Norway)	NCC
RCA4 (GFDL-ESM2M)	NOAA-GFDL (USA)	NOAA

3. Data and methods

3.1. Present climate data

Observed weather data have been collected from the General Directorate of Meteorology (DGM). The database includes daily minimum and maximum temperature (°C) and daily precipitation (mm) for the period 1981–2010. Precipitation data are from 141 rain gauges while temperature data is from synoptic stations in BF. It is worth to notice that a total of ten synoptic stations across BF is operated by the DGM for the measurement of climate variables such as solar radiation and sunshine duration (Fig. 1). Moreover, reliable long time series of temperature are only available at the synoptic stations. In the perspective of the crop model calibration at regional scale, European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Re-Analysis (ERA-Interim) data (Dee et al., 2011) for the period 2000–2010 and encompassing minimum and maximum temperature, and incoming shortwave radiation (MJ m^{-2} day^{-1}) have been retrieved (available at http://data-portal.ecmwf.int/data/d/interim_daily/), and then gridded to a 0.44° × 0.44° resolution.

3.2. Regional climate projection data

In the framework of CORDEX, the RCM group of the Swedish Meteorological and Hydrological Institute (SMHI) used the boundary conditions of eight GCMs (Table 1) from the Coupled Model Intercomparison Project – Phase 5 (CMIP5) to drive the latest version of the Rossby Centre Regional Climate Model – RCA4 over the African domain (Jones et al., 2011; Nikulin et al., 2012). From SMHI CORDEX-Africa, the RCM simulation database produced by SMHI, data on a daily basis including precipitation, solar shortwave radiation and minimum and maximum temperature have been retrieved. These data have been processed and then used as climate inputs in GLAM to simulate potential maize yields under future climate change scenarios. The dataset consists of control runs and projections based on the emission scenarios RCP4.5 and RCP8.5. RCP4.5 is a stabilization scenario in which total radiative forcing is stabilized after 2100, without overshooting the radiative forcing target level of 4.5 W/m^2 (≈650 ppm CO_2 equiv.) while RCP8.5 is a high emission scenario (i.e. increasing GHG emissions over time) corresponding to a rising radiative forcing pathway leading to 8.5 W/m^2 (≈1370 ppm CO_2 equiv.) by 2100 (Detlef et al., 2009; Allison et al., 2011; Riahi et al., 2011). Retrieved data range from 1989 to 2008 for the CTRL, and from 2011 to 2050 for the two RCPs.

3.3. Crop yield and soil properties data

Maize yields on province-level from 2000 to 2010 are used to calibrate the crop model GLAM. Yield data were provided by AGRHYMET Regional Center and the BF National Agricultural Statistic Division. The dataset contains annual rainfed crop production and estimated land area allocated for maize cropping. Given a specific province and year, yield (kg ha^{-1}) has been computed as a ratio between crop production (kg) and cropping land area (ha). The period 2000–2010 has been selected after a quality analysis of data. The quality analysis is based on data provider experience and data filtering. Data filtering is performed in two steps. First, from each of the two databases, only those years with a clear separation between rainfed and irrigated maize production have been selected. Then, for each selected year and province, the similarity in data (i.e. maize rainfed production and cropping land area) from the two databases has been checked in order to determine the matching time period which yields the lowest deviation. From this analysis, it is found that the difference between the two databases was less than 5% with no missing data for the period 2000–2010. After data filtering, a consistency analysis of data from the period 2000–2010 has benefited from the experience of data providers. Further, crop yields have been gridded at a resolution of $0.44^{\circ}\times 0.44^{\circ}$ by using a composite weighted average for provinces that share the same grid cell. No detrending has been applied to the data since this period 2000–2010 presented no significant trend in maize yields. For details, it is referred to Waongo et al. (2014).

Soil types and the corresponding hydrological properties are required by the crop model GLAM in the process of simulating the soil water balance through the crop growing period. Information on soil hydrological properties encompassed the lower limit (LL, corresponding to the wilting point), drainage upper limit (DUL, corresponding to the field capacity) and saturation limit (SAT, corresponding to the amount of water for a saturated soil). Soil data have been compiled and processed using the Harmonized World Soil Data (HWSD) of FAO (1991), following the procedure of Waongo et al. (2014). From HWSD, a 30 arc-second raster soil database, all soil types at 30 arc-second resolution across BF have been processed and further used to derive the dominant soil type for each grid cell of resolution of $0.44^{\circ}\times 0.44^{\circ}$. Finally, soil hydrological properties of the dominant soil types have been computed using soil property database from HWSD and an algorithm designed to compute soil water limits (Ritchie et al., 1999; Suleiman and Ritchie, 2001).

3.4. RCMs control run analysis

Climate data from RCMs have significant biases. The magnitude of the biases depends on the variable and the location. Uncertainties in GCMs whose outputs are used as boundary conditions to drive RCMs are partly sources of these biases. In addition, downscaling methods used in RCMs may induce additional biases. For regional climate change projections, uncertainties in GHG emission scenarios amplify RCM outputs biases. In general, RCM biases are usually higher for precipitation, particularly in data scarce regions such as West Africa (Cook and Vizy, 2006; Kim et al., 2014). Due to possible biases in RCMs which subsequently might affect the outcome of climate impact studies (Challinor et al., 2009), it is essential to characterize RCM accuracies before making use of RCM outputs for decision making support. To this end, biases of temperature and precipitation are analyzed for the RCM control runs for the whole BF and the three agroecological zones (AEZs) separately. The AEZs are defined on the basis of climatic zones described by Sivakumar and Gnoumou (1987) and a 30-yr mean annual rainfall distribution (Fig. 1) as follows:

(i) "North", which corresponds to the region where the mean annual rainfall is less than 600 mm and located in the North of BF. This region corresponds roughly to the sahelian zone and includes three synoptic stations.
(ii) "South", which corresponds to the region where the mean annual rainfall is more than 900 mm and is located in the South-West of BF. This region corresponds roughly to the South soudanian zone and includes four synoptic stations.
(iii) "Centre", which corresponds to the transition zone between North and South. The mean annual rainfall is more than

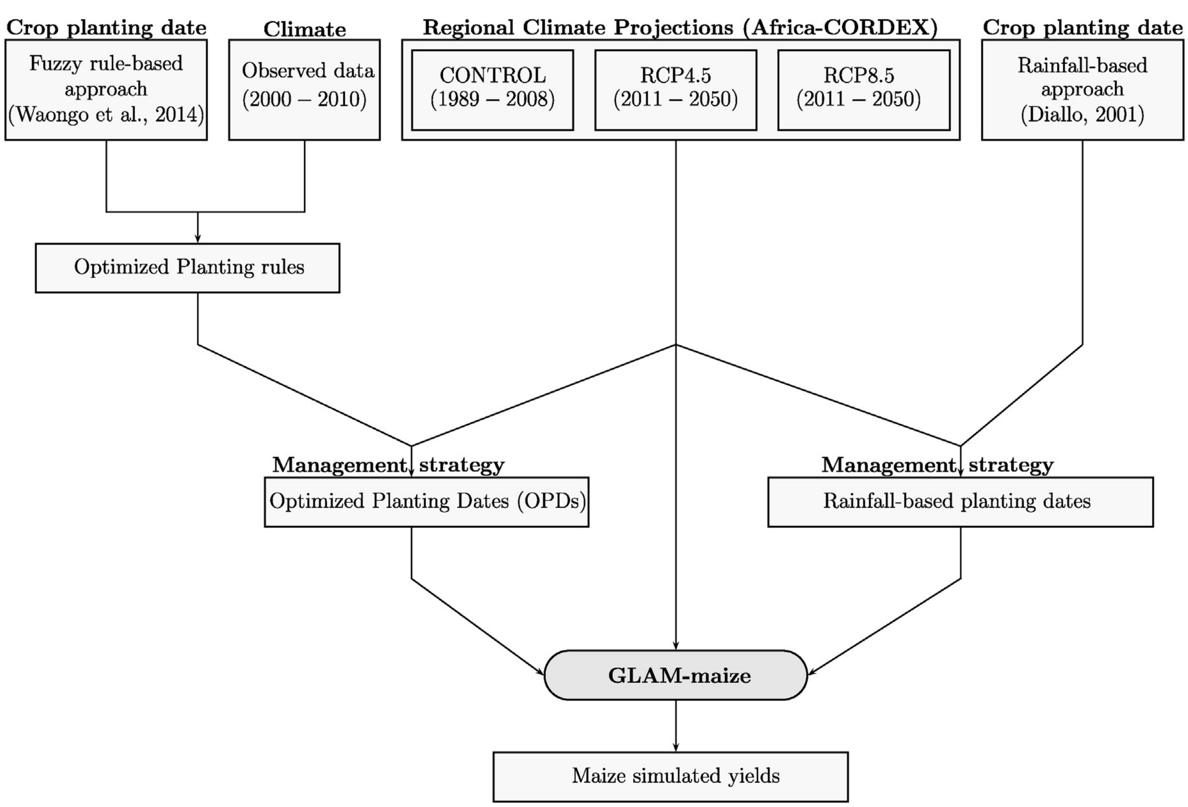

Fig. 3. Flowchart of potential maize yield simulation under regional climate projection and planting dates options.

600 mm and less than 900 mm. This region corresponds roughly to the Centre-North soudanian zone and includes three synoptic stations.

For each AEZ, the cycles of temperature and precipitation from the RCM control runs are analysed at monthly and seasonal (May–October) time scales. Synoptic stations per AEZ are thereby compared to their corresponding grid cells. In addition, Taylor diagrams are used to analyse temperature and precipitation, in order to draw conclusions about how well the RCMs control runs match the corresponding observations from synoptic stations in terms of correlation, root-mean-square difference (RMSD) and ratio of variances (Taylor, 2001). Taylor diagrams provide a way to summarize how closely climate model simulations match the observations. To this end, climate data for the period 1989–2008 from synoptic stations and RCMs grids cells matching the synoptic station locations have been used for the computation.

3.5. Large scale crop model

Crop models are designed to simulate the crop response to the environment, the soil and the management. In process-based crop models (PBCMs), crop growth is represented as the result of non-linear, dynamic relations between weather, soil water and nutrient, management and specific crop characteristics (Challinor et al., 2004; Hansen et al., 2006; van Bussel et al., 2011). Depending on the degree of crop growth details and spatial scale, PBCMs are discriminated in two groups: plot scale and large scale models. Unlike plot scale PBCMs, large scale PBCMs are designed to work directly at a scale compatible with global or regional climate model outputs. Due to the high demand of input data for plot scale PBCMs, large scale PBCMs are often used to investigate climate impacts on agriculture productivity in data scarce region such as SSA (Roudier et al., 2011; Webber et al., 2014).

In this study, the PBCM GLAM has been calibrated for maize yield simulation on a $0.44^{\circ}\times 0.44^{\circ}$ resolution. GLAM requires weather data on a daily basis (i.e. maximum and minimum temperatures, solar radiation and precipitation) as well as data on parameters describing crop and soil properties. Moreover, crop planting date is involved as management practice. GLAM simulates crop yield as a time varying fraction of the biomass. A harvest index rate parameter is used to convert the accumulated aboveground biomass into crop yield at the harvesting time. To account for the influence of non-climate parameters such as nutrient deficiency, non-optimal management, pest and diseases incidence in crop production, a unique yield gap parameter (YGP) is introduced in GLAM. For a specific crop and location, the YGP is quantified by the deviation between the simulated and observed yields. In GLAM, the YGP is determined by minimizing the root-mean-square error (RMSE) between observed and simulated yields. Simulated yields are computed for specified YGP values ranging from 0 to 1. Therefore, the optimal value of YGP for a specific location is the one corresponding to the lowest RMSE. Further, this optimal value of YGP is used as an input data bias correction parameter in GLAM for the specific location.

To calibrate GLAM for maize, selected key parameter sets of GLAM have been optimized using observed maize yields and a genetic algorithm optimization method (GA). The GA is based on the principles of genetics and natural selection (Holland, 1992). A GA applies genetic operators such as selection, recombination and mutation so that a population composed of possible solutions evolves under specified rules toward a global optimum solution. The first step in the calibration process using a GA is to create a sample of parameter sets using a uniform random distribution and a binary encoding. Each element or individual of the set is a binary string of length $p\times 2^{n}$, where p denotes the number of parameters to be calibrated in the GLAM model and n is the number of bits used to encode a given parameter. The second step is to evaluate the fitness function. The evaluation consist of transforming back all parameters of each individual in real numbers and then use them as GLAM inputs to simulate maize yields and subsequently compute the fitness. The fitness value for each individual is computed using statistics (i.e. RMSE and Pearson correlation coefficient) on observed and simulated yields. In order to account for the limited time series of observed yield data for the calibration, a cross-validation is performed at the evaluation step. After the fitness evaluation, GA's operators are applied in order to select individuals for mating. At this step of the selection, only the individuals with a higher (lower) fitness value will be selected more (less) frequently to the mating pool to yield offsprings for the next generation. The fitness evaluation and the selection steps are repeated for each new generation of individuals with the goal to evolve the set of parameters towards an optimum set based on the survival-of-the-fittest principle of nature. For more details on the different steps of GLAM calibration, the reader is referred to Waongo et al. (2014).

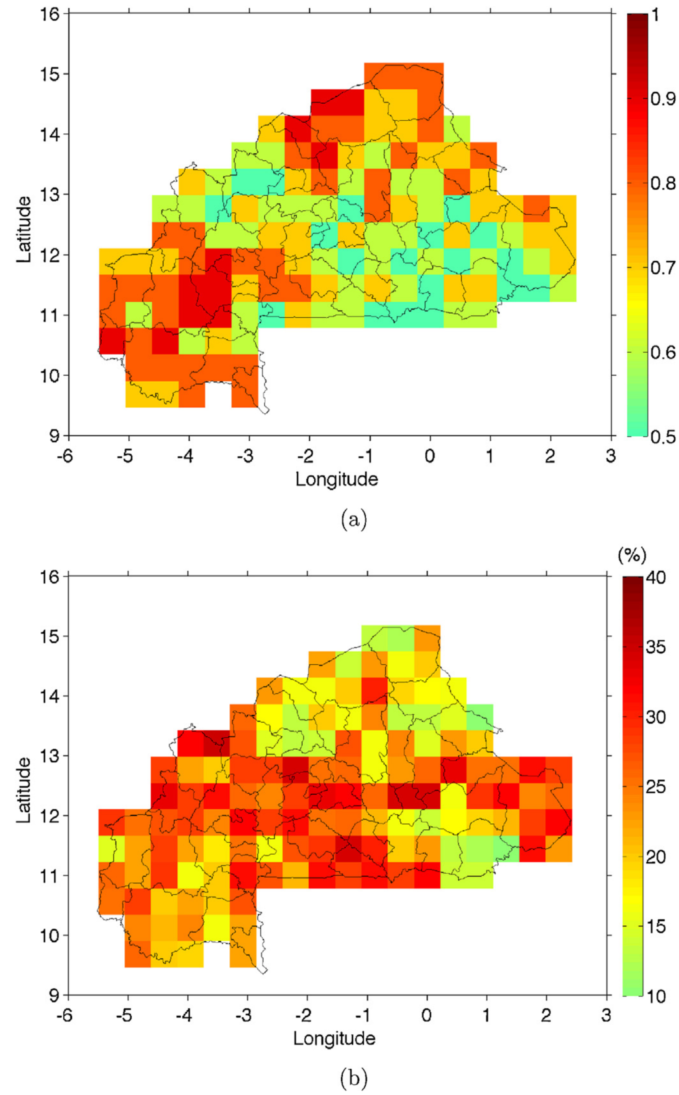

Fig. 4. Pearson correlation coefficient (a) and relative RMSE (b) between observed and simulated maize achieved by GLAM calibration.

3.6. Crop planting date optimization

Although the time for planting is a crucial management strategy in SSA, information on planting date is often not available.

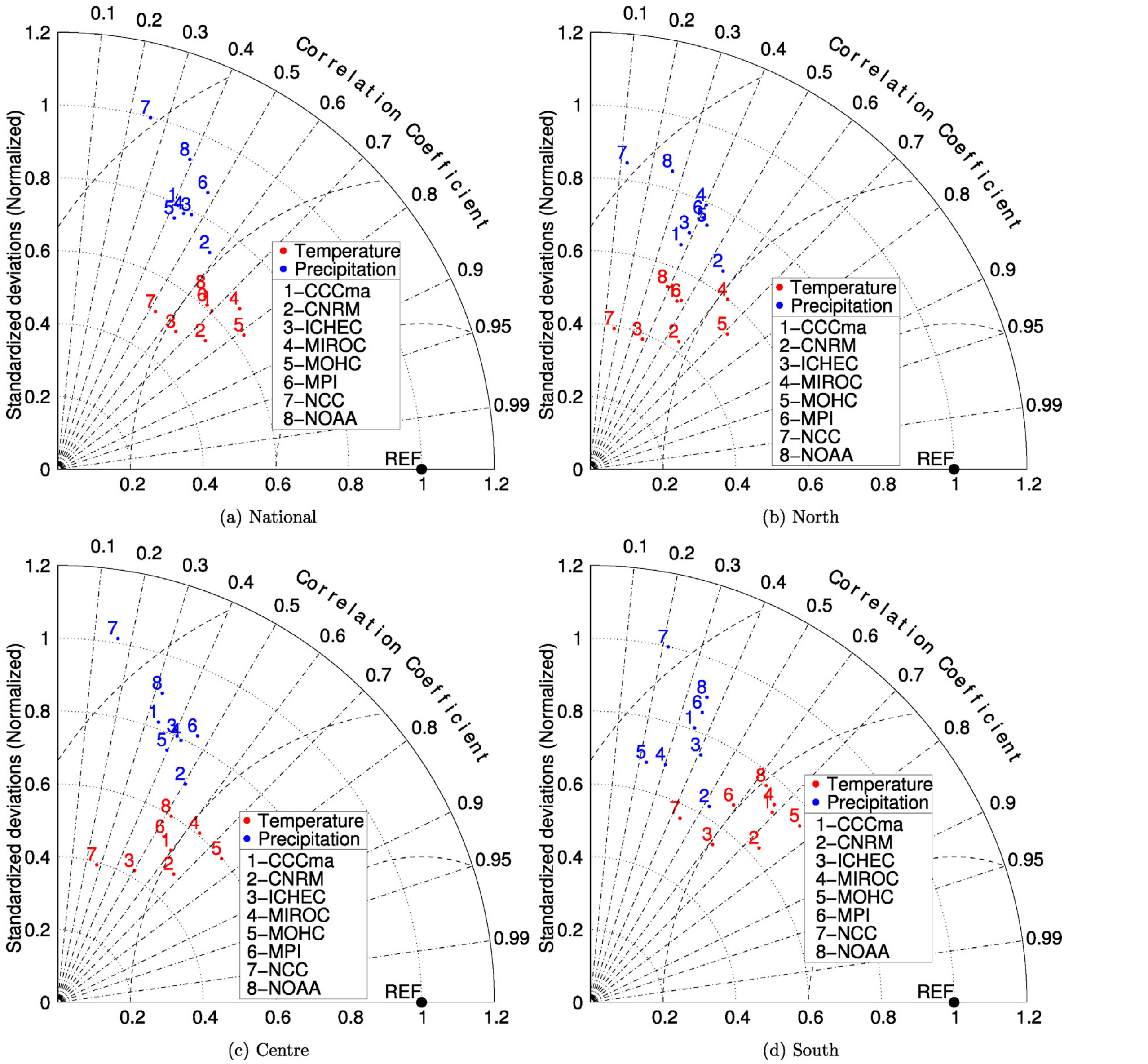

Fig. 5. Diagrams displaying temperature and precipitation statistics in comparison to observations for the AEZs and whole Burkina Faso. Statistics are based on RCM control runs data for period 1989–2008. The centered root-mean-square difference and the standard deviation of temperature and precipitation have been normalized. REF depicts observations derived from synoptic stations. Distances between REF location and RCM locations represent the values of RMSD.

The scarcity of planting date information in many regions over SSA can be partly explained by the fact that farmers use indigenous knowledges, particularly non-climatic reasons for sowing. For instance, although farmers are aware of the risk associated with early planting, Marteau et al. (2011) have found that in South-Western Niger some farmers plant crops without any synchronous or anterior rainfall events. Thus, with the aim to support farmers with scientifically sound information on planting dates, attempts have been made to estimate planting dates. From an agronomical point of view, suitable planting dates for a specific crop in SSA have to fulfill at least the following three criterions of crop water requirement (Laux et al., 2008; Waongo et al., 2014):

(i) The seedbed must be wet enough for sowing and the water requirements for germination and emergence have to be met. This depends on the specific soil type and crop.
(ii) Prolonged dry spells have to be avoided during the first stage of crop development since the crop is more vulnerable to water stress then. Severe water stress during the earlier stage of crop development may lead to crop failure and, therefore, requires resowing.
(iii) The length of the growing season has to fit with crop duration period in order to ensure sufficient water availability. This criterion is particularly important for water-limited regions such as SSA and for crops with reduced water stress resistance such as maize. For instance, latest planting dates which alleviate the risk of prolonged water stress through the rainy season, increase the risk of getting a shorter growing season and might result in a significant loss of production or, even worse a total crop failure in the reproductive stage (i.e. grain filling for maize occurring within the dry season).

Most of the crop planting date estimation methods fulfill the first two criterions by defining thresholds for rainfall amount,

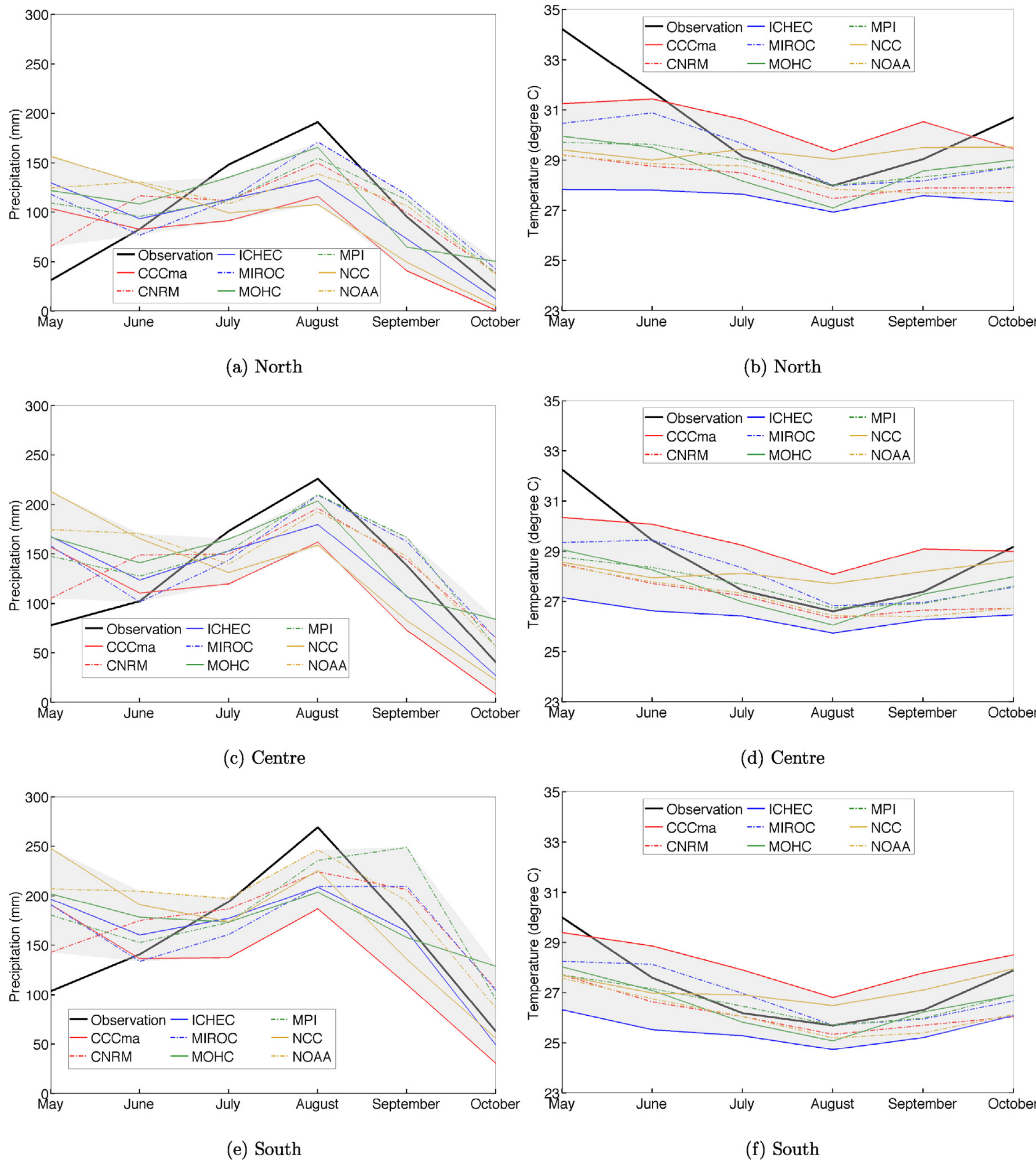

Fig. 6. Intra-seasonal cycle of RCM control runs precipitation (left) and temperature (right) for the AEZs. The black lines represent the monthly mean of observations from synoptic stations located in each AEZ. The light grey shading represents the range of variation of monthly precipitation amounts from all RCM control runs.

wet days and dry spell length from which potential planting dates can be computed (e.g. Stern et al., 1981, 1982; Dodd and Jolliffe, 2001; Diallo, 2001). These methods are generic since no information about crops has been included in the definitions. In a state-of-the-art approach in West Africa, Diallo (2001) defined the planting date as the first date after May 1, when at least 20 mm of rainfall accumulates over three consecutive days and when no dry spell of more than 10 days occurs within the next 30 days. These algorithms use Boolean logic to handle the different conditions to estimate planting dates.

Issues arise when using Boolean logic in these algorithms of the former approaches to deal with noisy measurement data of variables such as precipitation (Laux et al., 2009; Waongo et al., 2014). Moreover, these approaches inherently allow the computation of one single planting date rather than a planting time window. In order to account for those shortcomings, an optimized planting dates (OPDs) approach has been proposed recently (Waongo et al., 2014). This approach used a fuzzy rule to define planting dates. The fuzzy rule-based planting date is composed of three memberships which are the 5-day cumulative rainfall amount, the number of wet-day and the dry-spell length. Two parameters (i.e. a lower and upper bound) are required to define each of the three membership functions. In order to fully define a planting date, a defuzzification parameter is required. Thus, a total of seven parameters are used to define the fuzzy rule-based planting dates. For specified values of the seven parameters and a time series of daily

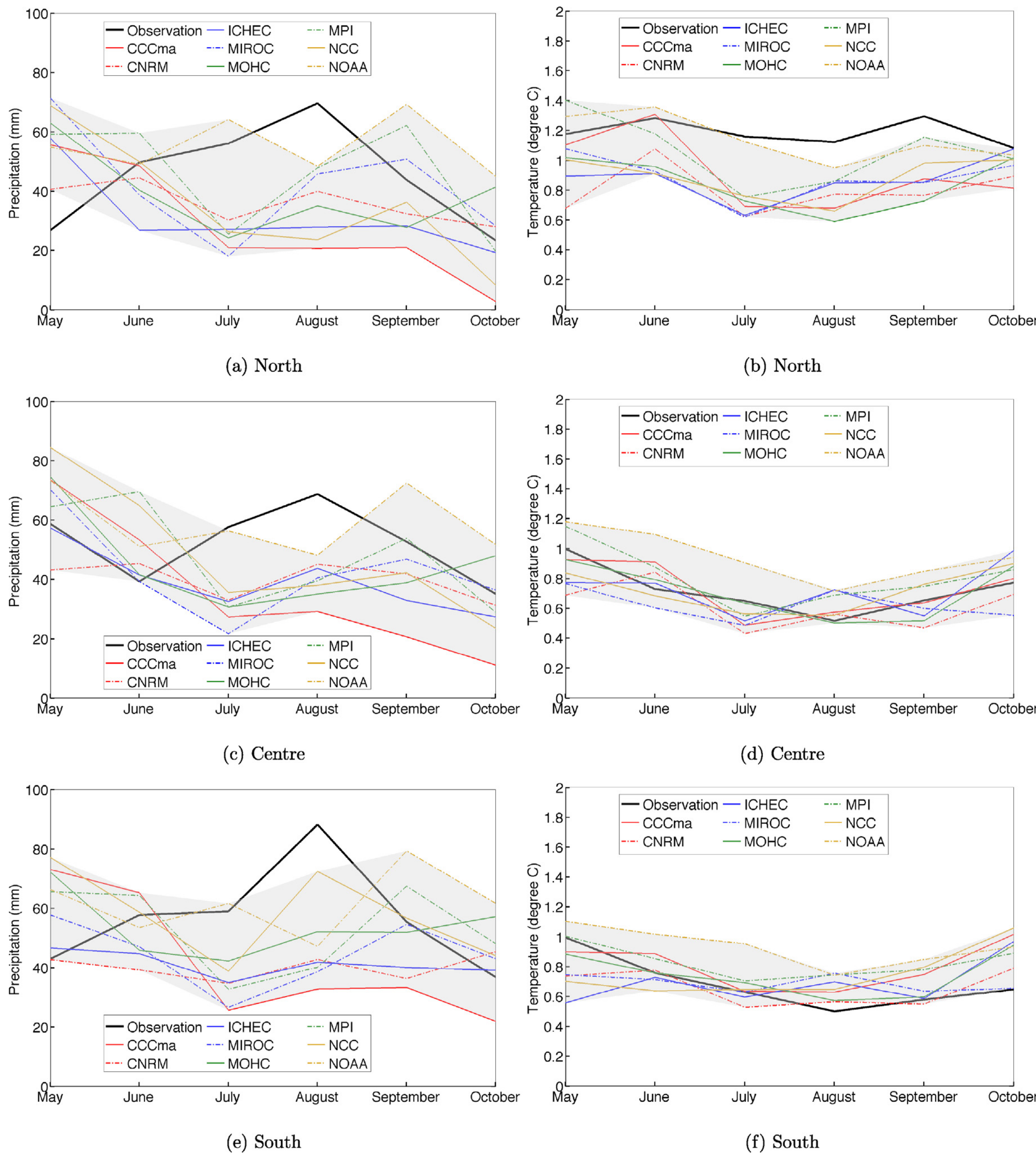

Fig. 7. Standard deviation of RCM control runs for monthly precipitation (left) and temperature (right) for the different AEZs. The black line represents the standard deviation of observations in each AEZ. The light grey shading represents the range of the standard deviations from all RCM control runs.

rainfall data from May to July, one can compute the planting dates. However, this computation yields a single planting date for a given year. In order to derive a suitable time window for planting, the approach of Waongo et al. (2014) used an ensemble of optimized fuzzy parameter sets to compute the OPDs. By coupling a GA with the crop model GLAM, the fuzzy rule-based planting dates and following the ensemble member principle, a 10-member ensemble of optimized fuzzy parameter sets is computed, thereby allowing the computation of a time window of the OPDs. For maize cropping across BF, the OPDs were found which have the potential to increase crop yield and reduce annual yield variability over the period 1980–2010.

In the present study, we performed the OPDs on a $0.44^{\circ} \times 0.44^{\circ}$ resolution. Likewise Waongo et al. (2014), the fitness function is defined in a way that the OPDs correspond to planting dates which yield higher potential crop yields and a reduced interannual yield variability over the period of simulation. Therefore, we assumed that higher fitness values should correspond to higher crop yields associated with lower coefficients of variation (CV). However, unlike Waongo et al. (2014), where the fitness function for each iteration is evaluated in a sequence of two steps, the fitness function (f) has been redefined slightly to reduce the computation time during the optimization process as follows:

$$f = \bar{Y}_{sim}^{(1-CV)}, \qquad (1)$$

where CV is the coefficient of variation in crop yield, $\bar{Y}_{sim}$ is the mean value of the simulated crop yield.

3.7. Maize yield simulation under climate change

One of the most popular methods for estimating the impacts of climate change on agriculture relies on crop models. First, the crop model is calibrated for a specific crop and selected region. Then, different climate change scenarios are run for each region given a particular management practice. In this study, the potential maize yield is simulated using the calibrated GLAM, climate data from eight RCMs and two planting date options. The simulations are performed for CTRL, RCP4.5 and RCP8.5 for each RCM, respectively. This results in eight crop yield simulations for CTRL and 32 crop yield projections. The planting date approaches of Diallo (2001) and Waongo et al. (2014) are used as management strategies. In this study, unlike the approach of Diallo (2001), Waongo et al. (2014) computes planting dates for climate change simulations in two steps. First, optimized location-specific planting rules are derived using a GA, the calibrated GLAM, observed climate data for the period 1989–2008 and the OPD approach. Second, the optimized location-specific planting rules are used in combination with the RCMs data to estimate the projected future OPDs. The simplified steps in the process of potential maize yield simulations under climate change are shown in Fig. 3.

4. Results

4.1. GLAM calibration

Present climate and observed maize yield data covering the period 2000–2010 are used to calibrate GLAM model for maize cropping across BF at a resolution of $0.44^{\circ}\times0.44^{\circ}$. In addition to the genetic algorithm process, a fivefold cross-validation is implemented for the simulation of yield in order to account for the limited size of the calibration period. The Pearson's coefficient of correlation (r) and the relative root means square error (rRMSE) between simulated and observed maize yield are used to measure the performance of the calibrated GLAM model. At a significant level $\alpha = 5\%$ (p-value < 0.05), r ranges between 0.52 and 0.93 (Fig. 4a). In general, the highest values of r are found in the northernmost and South-Western BF, while in the South-Eastern BF r values are lower than 0.70. The rRMSE values are lower than 40% over BF with lowest values in the Northern and South-Eastern BF (Fig. 4b).

4.2. RCMs temperature and precipitation analysis

Temperature and precipitation patterns for the RCM control runs are compared with observed data from synoptic stations in BF for the period 1989–2008. Fig. 5 summarizes the statistical relationship between RCMs simulations and observations. Statistics are calculated for four spatial domains, that is the whole BF (National) and the three AEZs. As shown in Fig. 5, the correlation coefficients (r) between RCMs simulations and observations are less than 0.60 for precipitation and 0.80 for temperature, irrespectively of the RCMs, variables (temperature and precipitation) and spatial domains. Among the RCMs, precipitation and temperature patterns from CNRM showed the highest correlation coefficients and the lowest RMSD while NCC showed the lowest correlation coefficient and the highest RMSD. However, the precipitation variance of the NCC model is similar to the observed variance. At the national scale, the precipitation patterns have been found to be similar for the models CCCma, ICHEC, MIROC and MOHC. However, there is a clear difference between the models in the three AEZs. These differences are more pronounced for the precipitation patterns than the temperature pattern.

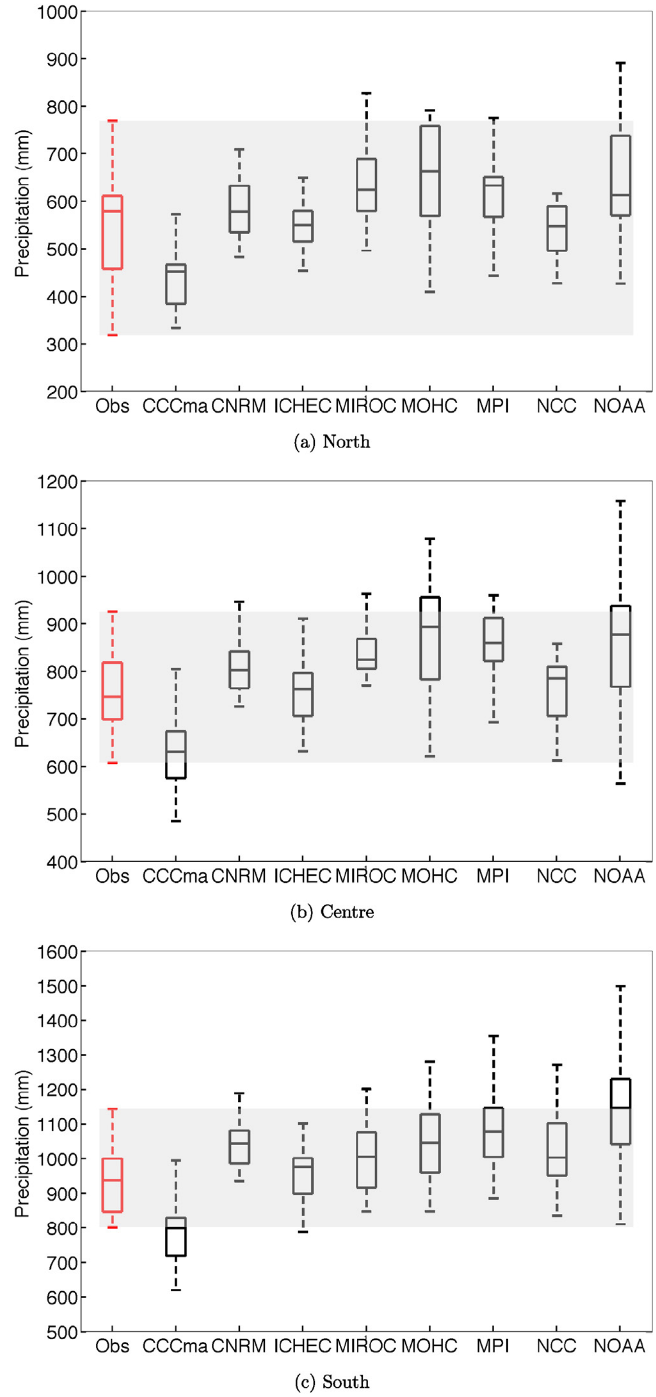

Fig. 8. Observation and RCM long-term seasonal precipitation amount distribution for the different AEZs. The red box-and-whisker plot represents the distribution of observed seasonal precipitation derived from synoptic stations for each AEZ for the period 1989–2008. The light grey shading highlights the range of variation of observations. X-axis denotes observations (Obs) and RCM labels.

Fig. 6 shows that all RCMs are, in general, able to capture the intra-seasonal cycle of mean temperature and precipitation during the main growing season (June–September). However, only the intra-seasonal variance of temperature are well captured by the RCMs (Fig. 7). Moreover, the variance of temperature is lower than the precipitation variance. For all AEZs, RCMs underestimate the mean and variance of monthly precipitation in August. With respect to RCMs, the model CCCma shows the largest biases for precipitation, particularly for the period July–October. The largest

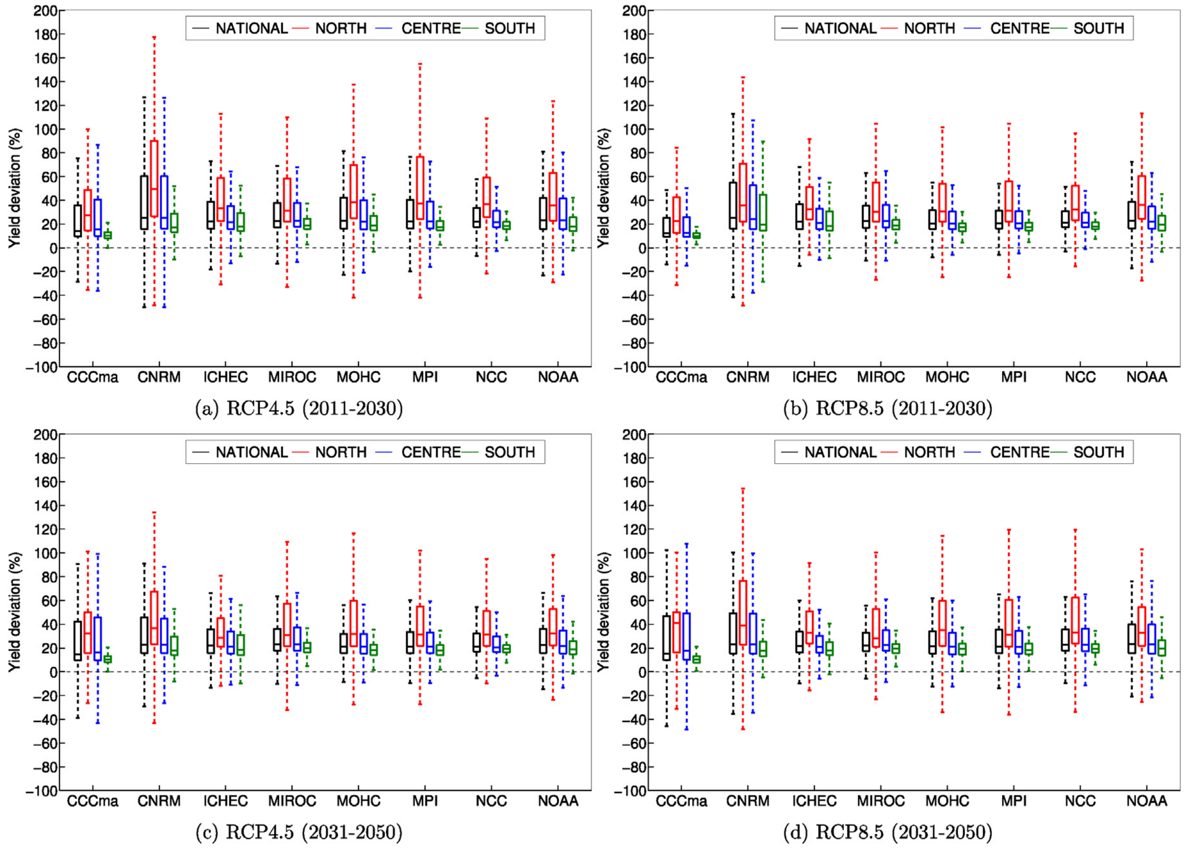

Fig. 9. Comparison between simulated maize yield obtained by OPD and Diallo (2001) under RCP4.5 and RCP8.5. For a given year, simulated yield obtained by Diallo (2001) is used as baseline to compute relative deviations (expressed in %) of yield obtained by OPD approach. *X*-axis denote RCM labels. The dotted horizontal line separated cases where the OPDs achieved higher potential yield than Diallo (2001) (boxplots above the dotted line) and cases where the OPDs achieved less potential yield than Diallo (2001) (boxplots below the dotted line).

biases of mean temperature are observed for the CCCma (i.e. an overestimation) and ICHEC (i.e. an underestimation) models during July–September. On average, the RCMs fail to reproduce precipitation and temperature in May. The RCMs strongly overestimate precipitation and underestimate temperature in May overall AEZs.

The seasonal precipitation gradient from the South to the North is reasonably captured by the RCMs (Fig. 8). Likewise Fig. 6 and 7, the underestimation of the mean and variance of precipitation over all AEZs by the CCCma model can be seen in Fig. 8. Moreover, Fig. 8 shows that the NOAA model tends to overestimate seasonal precipitation over the AEZs with a high variability of the seasonal precipitation amount. Since no systematic bias has been detected, we do not perform a bias correction for subsequent analyzes.

4.3. Comparison of future maize yields changes for two different planting date approaches

OPDs' impact on future maize production is evaluated in comparison with the planting date approach of Diallo (2001). The analysis is performed for two time periods (2011–2030 and 2031–2050) and different domains (North, Centre and South) as well as national scale. In general, as shown in Fig. 9, the OPDs achieve higher potential maize yield if compared to the approach of Diallo (2001) regardless of the RCMs, time periods and spatial domains. Indeed, the mean yield achieved by the OPDs is at least 15% larger than the mean yield achieved by the approach of Diallo (2001). Concerning the spatial scale, the mean and the variance of yield deviation decrease from the North to the South. For illustration, the high performance of the OPDs (yield deviation ≥30%) observed in the North is also associated with a high variability, regardless of RCM. In the South, yield deviation is, in general, greater than 0 and less variable.

4.4. Climate change impact on potential maize yield under the OPD strategy

The OPDs in combination with future climate projections from 8 RCMs have been used to estimate the climate change impacts on maize production. The spatial variability of potential maize yield for the period 2011–2050 has been evaluated under RCP4.5 (Fig. 10 and 12) and RCP8.5 (Figs. 11 and 13). Across RCMs, the change in mean yield varies between −23% and 34% from the baseline for the majority of grid cells. On average, a negative change in mean yield is observed. For the period 2011–2050, RCMs ensemble mean of yield change is −3.4% for RCP4.5 and −8.3% for RCP8.5. RCP4.5 shows an almost equally number of locations with negative and positive changes in the yield, regardless of the RCM (Fig. 14a). In contrast, a clear discrimination of mean yield changes is observed with RCP8.5, particularly for the period 2031–2050 where a negative change in the mean yield is dominantly observed for six out of eight RCMs (Fig. 14b). With respect to the RCMs, a decrease in yield is observed for the CCCma and MIROC models for the majority of locations in the South-West and Centre-East of BF, irrespectively of the RCP and period. However, the ICHEC model shows a higher positive change (>40%) of mean yield in the South-West of BF, regardless of RCP and period. In the North and Centre-East, RCP8.5 yields a more pronounced decrease in mean yield during the period 2031–2050 for the CNRM, ICHEC, MOHC, MPI and NOAA models.

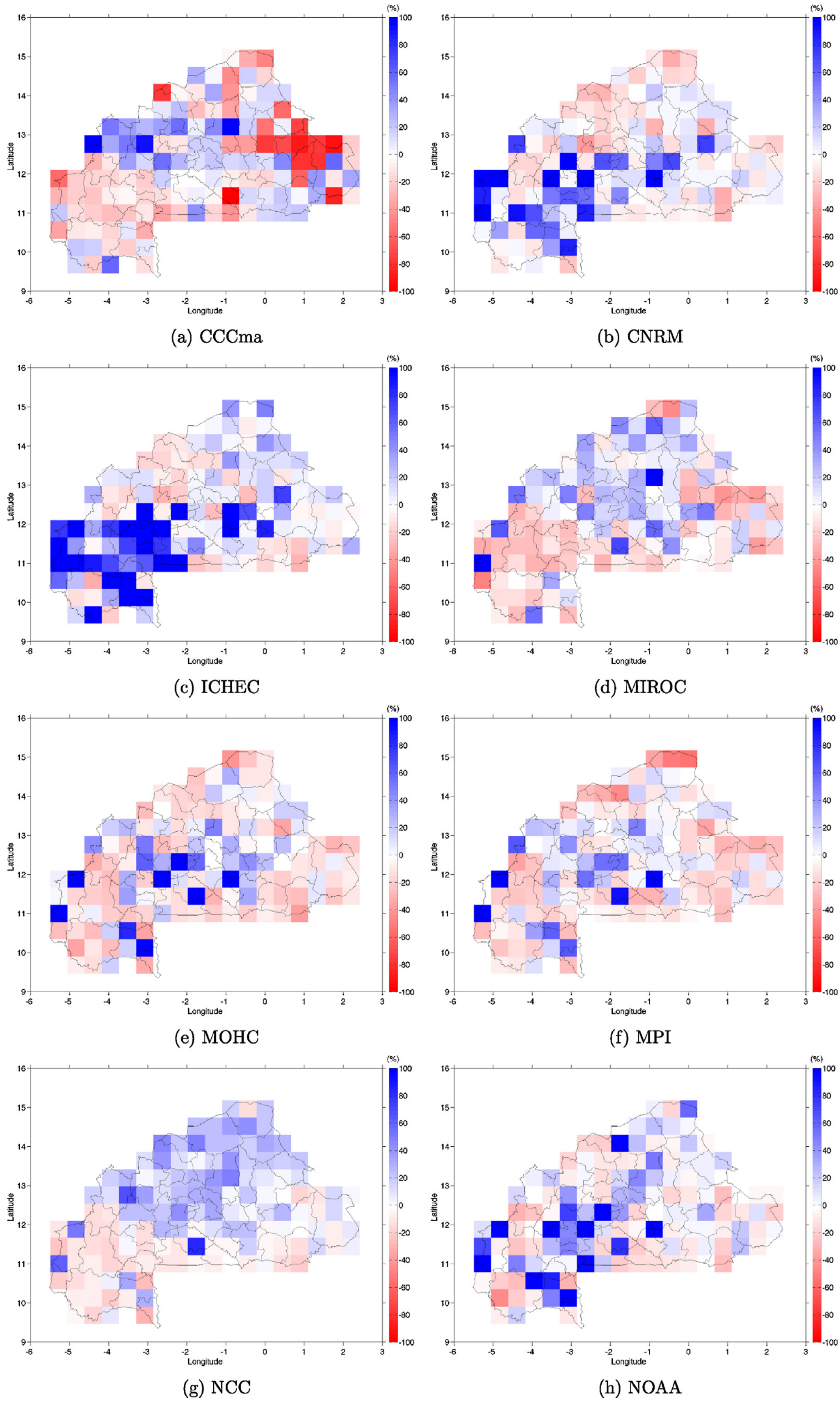

Fig. 10. Attainable maize mean yield changes for eight RCMs under the emission scenario RCP4.5 and the OPDs for the period 2011–2030. The change in yield is expressed in % of the mean yield obtained by RCM control runs (period 1989–2008).

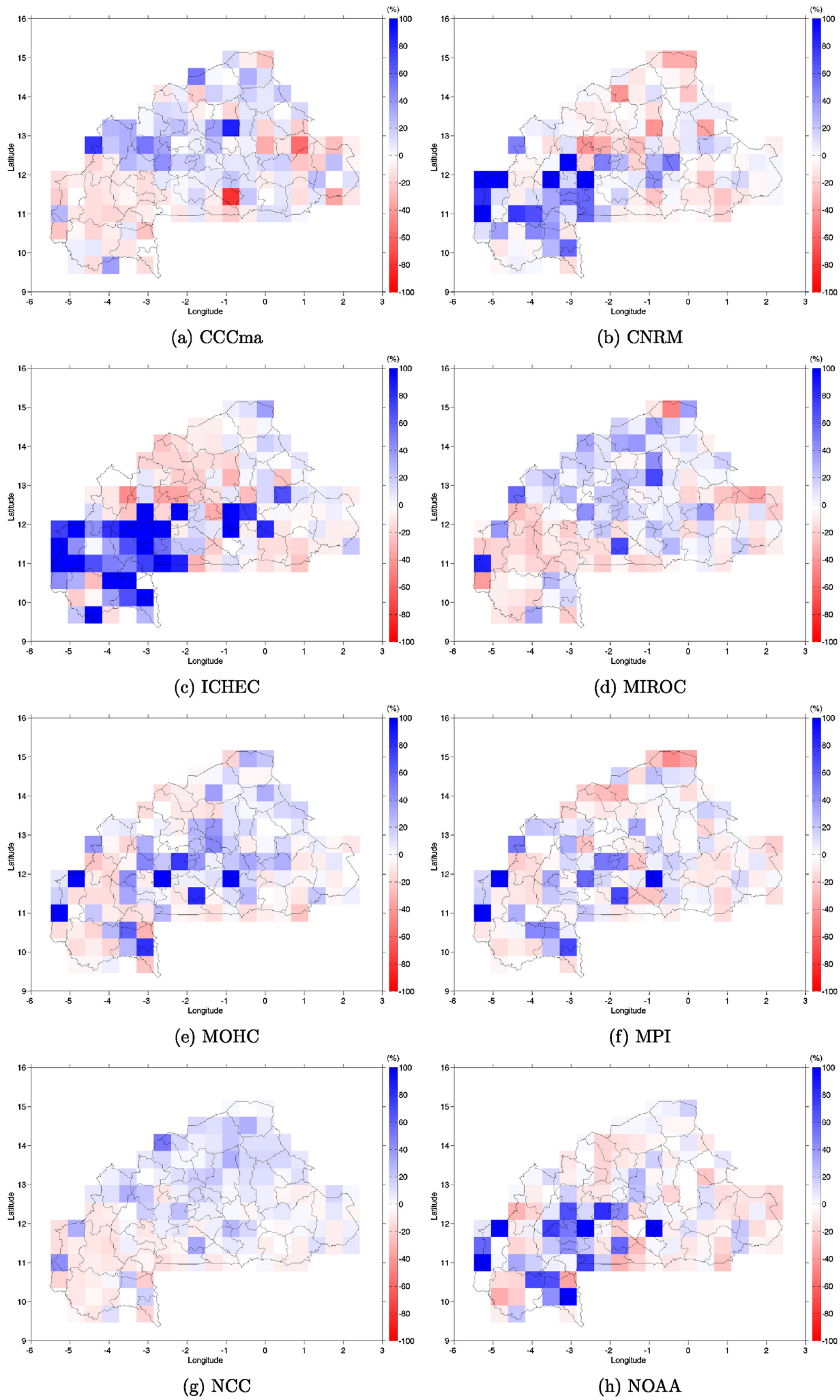

Fig. 11. Attainable maize mean yield changes for eight RCMs under the emission scenario RCP8.5 and the OPDs for the period 2011–2030. The change in yield is expressed in % of the mean yield obtained by RCM control runs (period 1989–2008).

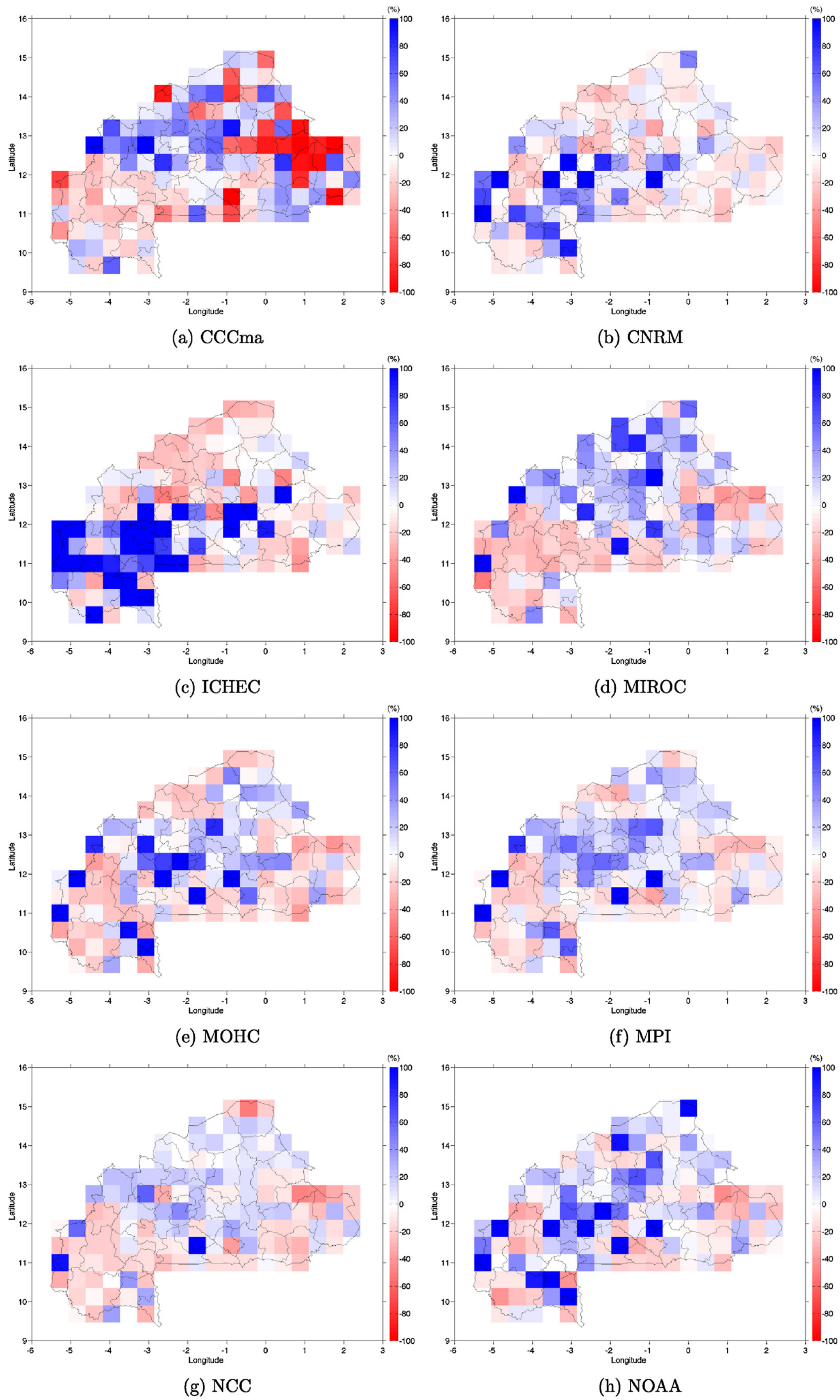

Fig. 12. Attainable maize mean yield changes for eight RCMs under the emission scenario RCP4.5 and the OPDs for the period 2031–2050. The change in yield is expressed in % of the mean yield achieved by RCM control runs (period 1989–2008).

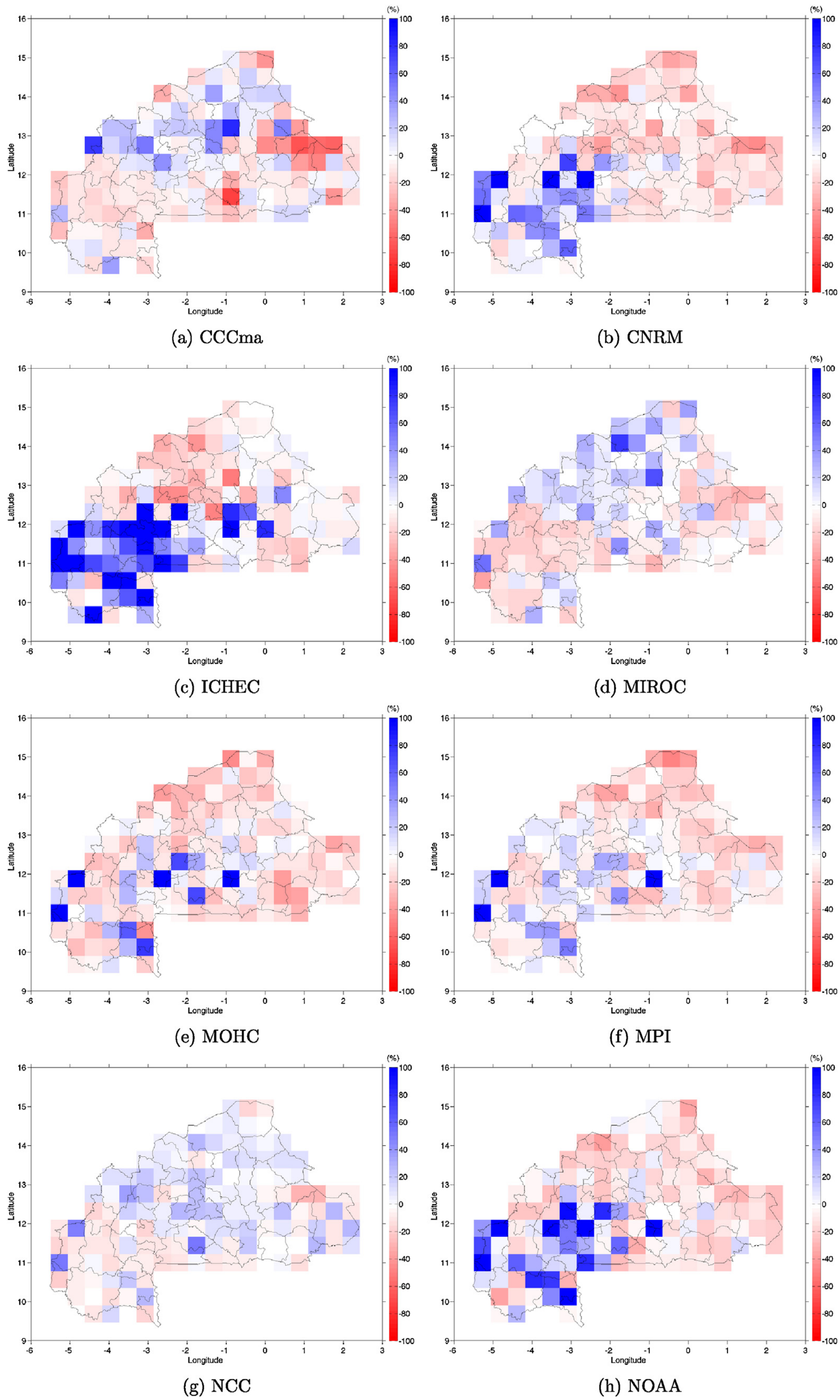

Fig. 13. Attainable maize mean yield changes for eight RCMs under the emission scenario RCP8.5 and the OPDs for the period 2031–2050. The change in yield is expressed in % of the mean yield achieved by RCM control runs (period 1989–2008).

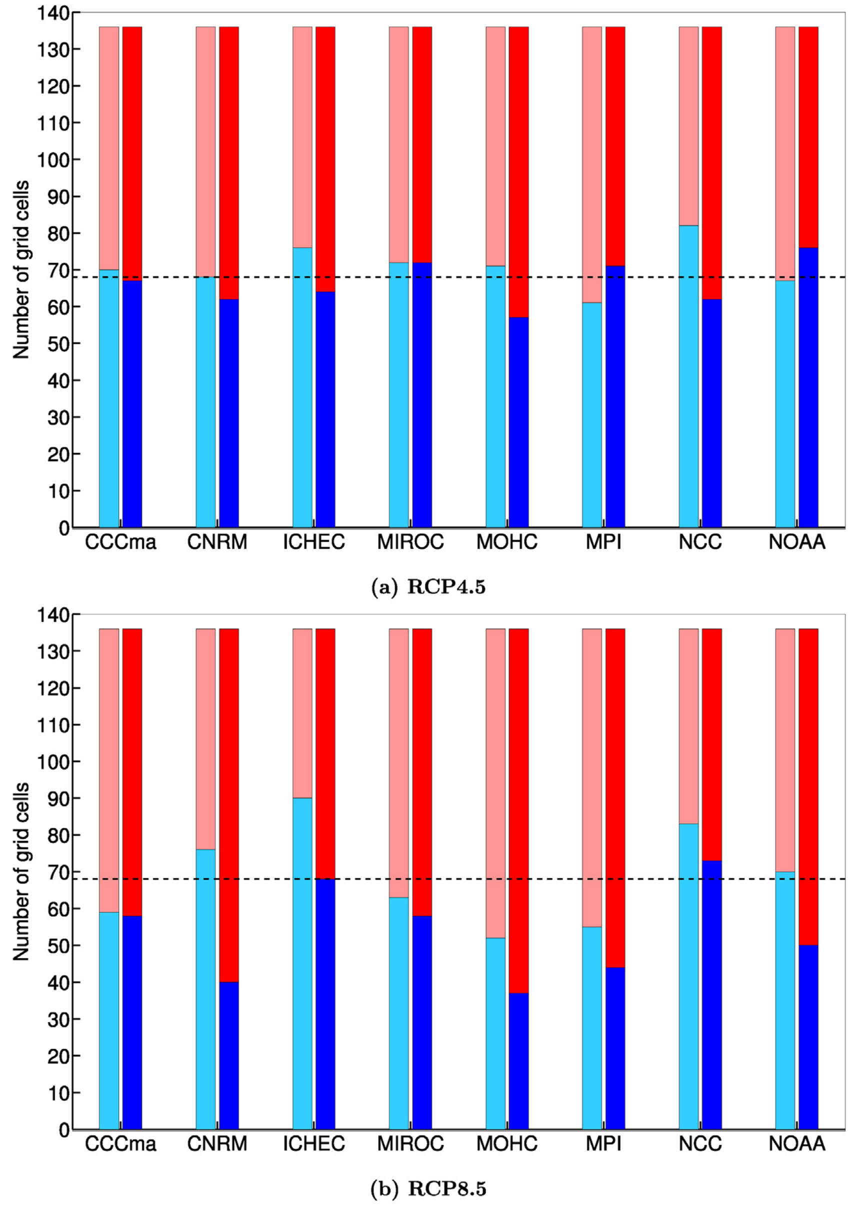

Fig. 14. Number of locations affected by a negative change (red and light red) and a positive change (blue and light blue) of simulated yield in comparison to the baseline 1989–2008. Light red and light blue boxes represent the period 2011–2030 while red and blue boxes represent the period 2031–2050. *X*-axis represents RCMs and the horizontal dotted line represents the half of the total number of grid cells (136) in the study domain.

5. Discussion and conclusions

Based on regional climate change scenarios and two planting date approaches, maize yield has been simulated using the process-based GLAM model. The results showed that the OPD approach achieves significantly higher potential yield compared to the planting date approach of Diallo (2001). In agreement with Waongo et al. (2014), the findings confirmed the potential benefit of the OPDs in BF. Unlike crop-generic and rainfall based methods (e.g. Stern et al., 1981, 1982; Sivakumar, 1988; Dodd and Jolliffe, 2001; Diallo, 2001), the OPD approach combines climate (i.e. rainfall, temperature, solar radiation) with soil and crop information in order to derive planting dates. Therefore, planting dates can be derived for different crops and locations. However, the spatial resolution of the derived OPDs commensurates with RCMs and, therefore, might not be well suited for decision-making at local scale or farm-level which need locally refined climate information and crop management.

This study assessed also the impact of climate change on maize productivity in conjunction with the OPD approach as adaptation strategy. The results show that on average, potential maize yield is expected to be decreased in the future for the majority of locations across BF, particularly for RCP8.5 during the period 2031–2050. With regards to the finding, planting dates based on the OPD approach have to be associated with others management strategies in order to be able to strengthen climate change adaptation. The fact is that there are not many decisions in farming that are simple based on a single factor nor are they made in line with a purely tactical response to current information. For long-term adaptations, farmers need to jointly adapt several farming practices to adequately respond to climate risks. However, in SSA, the constraints imposed by poor supportive policies and the extreme poverty of farmers are still the major limitation for the adoption of various strategies (Antwi-Agyei et al., 2013), thereby making adaption to climate change more complex in this region. It is also worth to highlight that this study evaluates the potential impacts of climate change on maize production based on one single RCM (i.e. RCA4) which is driven by eight GCMs (Nikulin et al., 2012). Moreover, potential management strategies (e.g., adoption of new crop varieties, enhancement of the use of fertilizers, development of irrigation options) which decision-makers might strongly promote and farmers might adopt in the future to cope with climate change are not considered for the long term yield simulations.

Prior to maize yield simulations, the RCM control runs were checked for their biases in representing the seasonality of precipitation and temperature. Compared to synoptic observation data, the RCM control runs do reasonably represent the seasonal cycles of mean precipitation and temperature and no large biases except for May were detected. However, RCMs strongly underestimate the variance of monthly precipitation in August. Since May does not correspond to the suitable planting time in Burkina Faso, no bias correction has been performed in this study. The use of the raw RCM data without applying additional bias correction also has the advantage that the disruption of the physical consistency between the different variables (here: precipitation, temperature) is avoided.

In the face of increasing climate variability and climate change, multi-model ensemble simulations (multiple RCMs driven by multiple GCMs and emissions scenarios) are necessary to quantify the uncertainties of impacts of possible climate realizations on crop production. However, only RCMs data from SMHI-Africa CORDEX were available at the time of this study. Therefore, with the objective of enhancing climate-related risk adaptation options, further studies might be necessary to capture the whole range of climate uncertainties.

Besides those long-term adaptation strategies, the OPD approach can also be used in combination with seasonal climate forecasts to provide planting date information for the current season. In SSA, the seasonal climate outlook (SCO) is made routinely and provides mainly tercile probabilities (below normal, near normal, above normal) of the three-monthly rainfall amount for the upcoming season. Although economic values of SCO at farm level have been found in SSA (Sultan et al., 2010), the adoption of the current seasonal climate outlook by farmers is low. One of the main reasons for the low uptake has been highlighted by Ingram et al. (2002), which found that farmers expressed a strong interest in receiving SCO, but they were much more interested in receiving information on the onset and cessation of rainy season, and dry spell probability during the growing season. Therefore, it is obvious that farmers concern is how to limit the risk of crop failure and to sustain their crop production. Thus, the prediction of the OPDs with a lead-time of few weeks might be of high relevance for farmers and guides them in the choice of crops and the planning of labor and on-time preparation of farm lands. The prediction of OPDs will therefore require the use of seasonal rainfall forecast products at daily resolution. It should be noted that prior to the operational usage of these products, retrospective forecast data can be used to assess their performance.

Although the added value of the OPDs has been demonstrated in this and a previous study of Waongo et al. (2014), on-field validation is required before any operational use of this approach. Moreover, in light of the limited skill of the seasonal prediction of the local-scale onset of the rainy season (e.g. Marteau et al., 2009), also the predictability of the OPDs has to be investigated and tested extensively over SSA.

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