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Impact of climate change on agricultural productivity under rainfed conditions in Cameroon—A method to improve attainable crop yields by planting date adaptations

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ABSTRACT

Rainfed farming systems in sub-Saharan Africa are suffering from low productivity. Prolonged dry spells and droughts often lead to significant crop losses, a situation that is expected to be exacerbated by climate change. In this study, the impact of climate change on attainable yields of maize and groundnut, as major alimentary crops in sub-Saharan Africa, is evaluated at five stations in Cameroon under rainfed conditions. It is focussed on the contribution of future climate change in terms of the direct fertilisation effect of the expected CO_2 alteration and the indirect effects of the expected temperature and precipitation change. As improved agricultural management practices in rainfed systems are crucial to increase agricultural productivity, the impact of the planting date is analysed in detail. For this purpose, a fuzzy logic-based algorithm is developed to estimate the agriculturally relevant onset of the rainy season (ORS) and, thus, the optimal planting date. This algorithm is then connected to the physically based crop model *CropSyst*, hereinafter referred to as *optimal planting date following crop modelling system*. A Monte Carlo approach is used to optimise the ORS algorithm in terms of maximising the mean annual crop yields (1979–2003). The *optimal planting date following crop modelling system* is applied to past and future periods, mainly for two reasons: (i) to derive optimal fuzzy rules and increase mean attainable crop yields; and (ii) to reliably estimate the impact of climate change to crop productivity with ('optimal planting date scenario') and without planting date adaptations ('traditional planting date scenario').

It is shown that the fuzzy rules derived for assessing the optimal planting dates may allow for significantly increased crop yields compared to the existing planting rules in Cameroon under current climatic conditions, especially for the drier northern regions. A change in the climatic conditions due to global warming will reduce the growing cycle and, thus, the crop yields. However, the positive effect of CO_2 fertilisation is likely to outweigh the negative effects of precipitation and temperature change for the 2020s and partly for the 2080s. When additionally considering planting date adaptations, groundnut yield is expected to increase for the 2020s and the 2080s, with maximum yield surpluses of about 30% for the 2020s compared to the extended baseline period. For maize, crop yield is likely to increase (decrease) for the 2020s (2080s) by approximately 15%. For the driest stations analysed, the negative impacts of temperature and precipitation change could be mitigated significantly by planting date adaptations.

1. Introduction

Eighty-two percent of the cropland worldwide is cultivated under rainfed conditions. The importance of rainfed agriculture varies regionally, but it is of utmost significance for sub-Saharan Africa. There, agriculture accounts for 35% of GDP and employs 70% of the population (Worldbank, 2000). Approximately 95% of the total cropland is managed under rainfed conditions (FAOSTAT, 2005, http://faostat.fao.org). The spatial and temporal variations of crop yield may have a profound impact on the national economies of sub-Saharan countries, which are primarily dependent on the agricultural sector.

1.1. Rainfall variability and agricultural productivity under rainfed conditions

The high spatial and temporal variability of rainfall, reflected by dry spells and recurrent droughts and floods, may be considered the most important factor affecting agricultural productivity in sub-Saharan Africa. The intra-seasonal and inter-annual vari-

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ability is often given as the main reason for crop failure and food shortages (e.g. Sivakumar, 1988; Paeth and Hense, 2003; Usman et al., 2005; Sultan et al., 2005; Mishra et al., 2008). Wheeler et al. (2005) demonstrated the simulated effect of evenly and unevenly distributed intra-annual rainfall on crop yield, independently of the total annual amount. Plant water availability strongly depends on the onset, cessation, and length of the rainy season. The onset of the rainy season (ORS) is the most important variable for agricultural management (e.g. Stewart, 1991; Ingram et al., 2002; Ziervogel and Calder, 2003). It directly affects farming management practices, especially planting which, in turn, significantly affects crop yield and the probability of agricultural droughts (Kumar, 1998). For sowing, it is important to know whether the rains are continuous and sufficient to ensure enough soil moisture during planting and whether this level will be maintained or even increased during the growing period to avoid total crop failure (Walter, 1967). Planting too early might lead to crop failure and, in turn, planting too late might reduce valuable growing time and crop yield. However, there is still no consensus in literature about the question of how much rain over which period defines the ORS for agro-climatological impact studies. The definition of Stern et al. (1981), hereinafter referred to as the *Stern definition*, is possibly the most widespread rainfall-based definition used to estimate local ORS dates. This approach states that the wet season has started when, for the first time after March 1st, 25 mm of rain falls within 2 consecutive days, and no dry period of 10 or more days occurs in the following 30 days. Prior to its application, however, the user must adapt these criteria, which strongly depend on local weather conditions, soil types, the evaporative demands of crops, cropping practices, etc. Laux et al. (2008) extended the *Stern definition* to regional usability in a case study for the Volta basin (West Africa) using a fuzzy logic approach. Furthermore, they derived trends of the ORS dates and developed methodologies for predicting the ORS on the regional scale. Recommendations for agricultural decision support, including maps of optimal planting dates and rainfall probabilities for the Volta basin, are presented in another paper (Laux et al., 2009b). Based on the *Stern definition*, Kniveton et al. (2009) performed a grid-based analysis of the temporal and spatial ORS variability on a continental scale covering Africa and parts of southern Europe and the Middle East as a function of different definition parameterisations.

Similarly to the *Stern definition*, instances of definition approaches with fixed definition parameterisations are presented by Marteau et al. (2009) for the west and central Sahel (Senegal, Mali, and Burkina Faso), Mugalavai et al. (2008) for Kenya or Raes et al. (2004) for Zimbabwe. A comparison of existing approaches to estimating the ORS for Nigeria is given by Ati et al. (2002).

1.2. Impact of climate change on agricultural productivity

Providing sufficient food for the world's increasing population is becoming more difficult as land, water, and vegetative resources are progressively degraded through prolonged overuse. In the future, this difficulty will be exacerbated by climate change (Rosenzweig and Hillel, 1998). Climate change alters the biophysical environment in which crops grow and howcrops respond to some factors of climate change, such as CO_2, temperature, precipitation, and evapotranspiration.

Atmospheric CO_2 accumulation without changing temperature and precipitation patterns, might likely be of benefit for crop production. Plants commonly respond to higher levels of CO_2 with increased rates of photosynthesis, because CO_2 absorption is facilitated by the stronger gradient between the atmosphere and air spaces inside the leaves. C3 plants, such as rice, soybean, and groundnut, exhibit lower rates of net photosynthesis than C4 plants (e.g. maize) at the current CO_2 level ($\approx$ 385 ppm). At elevated levels, C3 plants may become more competitive than C4 plants, due to larger increases in photosynthetic rates. In addition to the enhanced photosynthesis rates, plants respond with a partial closure of their stomata, thus reducing transpiration per unit leaf area and improving their water use efficiency (Rosenzweig and Hillel, 1998). However, a significant impact in terms of the direct fertilisation effect of CO_2 cannot be expected before 2050 when CO_2 is likely to reach twice the preindustrial level (Nakicenovic and Swart, 2000).

Initial studies dealing with the climate change impact on crop productivity focussed on the effects of an increased CO_2 level, followed by studies that additionally took the change of average climate conditions into account, such as a rise in the mean global temperature and/or change in rainfall (Porter and Semenov, 2005). Rosenzweig and Parry (1994) combined data from several individual studies on a regional/national level to draw a global picture of the simulated change in crop yield associated with different climate change scenarios. Additionally, they simulated the economic consequences of the simulated crop yield changes using a world food trade model. They found negative changes to the modelled yield in low latitudes, where many developing countries are located, and is contrary to the increased yield in middle and high latitudes, the predominant location of developed countries.

Estimates of climate change impacts on agricultural productivity yields are often characterised by large uncertainties that reflect an ignorance of many processes and hamper efforts to adapt to climate change (Lobell and Burke, 2008).

According to Diepen and van der Wall (1996), these processes/factors can be categorized as:

(i) abiotic factors, such as soil moisture, soil fertility, weather;
(ii) farm management factors, such as soil tillage, sowing date, harvesting techniques;
(iii) land development factors, such as irrigation;
(iv) socioeconomic factors, such as distance to markets, population pressure, education levels; and
(v) catastrophic factors, such as droughts, floods, and pests.

A key to reducing these uncertainties is the improved understanding of the relative contribution of each individual factor (Lobell and Burke, 2008).

As crops are subject to combinations of stress factors that affect their growth (and yields) and respond non-linearly to changes in their growing conditions, Porter and Semenov (2005) stressed the importance of climatic variability. According to the IPCC (2001), crop yield responds to three sources of climatic variability:

(i) change in the mean conditions, such as annual mean temperature and/or precipitation;
(ii) change in the distribution, such that there are more frequent extreme events (physiologically damaging temperatures or longer drought periods); and
(iii) a combination of changes of the mean conditions and the variability.

According to Monteith (1981), the two largest causes of yield variation are temperature and rainfall. Their independent effects are three to four times larger than those caused by the variation in solar radiation. The increased variation and changes in mean temperature and precipitation are expected to dominate future changes in climate, as they affect crop productivity. Various studies dealing with the effects of climatic variability have pointed to the conclusion that an increased annual variability of weather, as expected due to global warming, causes an increased variation of yields (e.g. Semenov et al., 1993; Porter and Semenov, 2005). Short-term extreme temperatures, often referred to as crop temperature thresholds in the literature, are known to have non-linear yield-reducing effects on major crops, depending on the vegetation stages (Porter and Semenov, 2005). Rosenzweig and Hillel (1993) found an empirical relationship between daily $T_{max} > 30\,^{\circ}C$ during the growing season and maize yield in the USA. A similar relationship was found for Cameroon (Tingem et al., 2008).

1.3. Impact of planting date on agricultural productivity

In terms of agricultural management strategies, the planting date is known to be of central importance for agricultural productivity. Many studies have dealt with the impact of the planting date exclusively (e.g. Carlson and Gage, 1989; Egli and Bruening, 1992; Matthews et al., 1997; Kombiok and Clottey, 2003; Mandal et al., 2005; Lopez-Bellido et al., 2008; Soler et al., 2008; Baldwin and Cossar, 2009; Barradas and Lopez-Bellido, 2009; Blanche and Linscombe, 2009; Egli and Cornelius, 2009; Fagundes et al., 2009; Garcia et al., 2009) or in combination with other management factors (e.g. Ghosh, 1998; Tubajika et al., 2001; Pedersen and Lauer, 2004; Soltani and Hoogenboom, 2007; Kamara et al., 2009).

Instead of analysing the impact of systematically shifted ('fixed') planting dates on crop yields, optimal planting rules will be derived in this study, which allow for inter-annually varying planting dates.

1.4. Aims of this study

The inherent variability of weather, especially intra-seasonal and inter-annual rainfall variability, but also imperfect agricultural decisions, often prevent crop yield from reaching its potential in rainfed regions, such as Cameroon. These regions are most vulnerable to climate change, which is expected to aggravate food security in sub-Saharan Africa. Therefore, the aims of this study are to:

(i) Develop an *optimal planting date following crop modelling system* as a method to improve existing ORS definitions. For the first time, this method takes the intra-seasonal rainfall variability into account to derive optimal planting rules, and hence, to increase simulated crop yield.
(ii) Estimate the potential crop yield increase in Cameroon by planting date adaptation under current and future climatic conditions.
(iii) Analyse the impacts and uncertainties of climate change on crop productivity at different locations in Cameroon in terms of changing rainfall, temperature and CO_2 concentrations, with and without a planting date adaptation.

2. Methodologies

2.1. Study region characteristics and observational data

Cameroon is located between 2°N and 13°N and covers an area of about 475, 440 km^2. It is ranked 172 out of 229 countries in the world in terms of per capita income. Nearly 40% of the population live on less than 2 US$ per day. The agricultural sector accounts for 45% of the GDP and occupies about 80% of the labour force. Most of the country's poor people live in rural areas where small-scale subsistence farming under rainfed conditions prevails.

The study region is characterised by highly contrasting physical features, including approximately 400 km of coastline and mountainous regions with altitudes up to 4000 m (Fig. 1). Reflecting the topography and latitudinal range, very steep gradients of isohyets occur in the humid (> 4000 mm annual rainfall) equatorial region in the south-west and the semi-arid (≈ 400 mm annual rainfall) region in the north (ORSTOM, 1996).

The intra-seasonal distribution of rainfall is modulated by the shift of the Intertropical Convergence Zone *ITCZ*. In the northern regions of Cameroon between 7°N and 10°N (Garoua, Ngaoundéré), only one rainy season occurs, lasting roughly from May to October, whereas a bimodal rainfall distribution exists in the equatorial south (Bamenda, Batouri and Yaoundé). The first rainy season, which is longer and more profitable, ranges roughly from March to July and the second one from August to November. The growing season is strongly related to the rainy season, and following the mean regional ORS, the traditional planting date for the equatorial south is 15 March and 15 August. In the northern region it is 15 May (Ndemah, 1999).

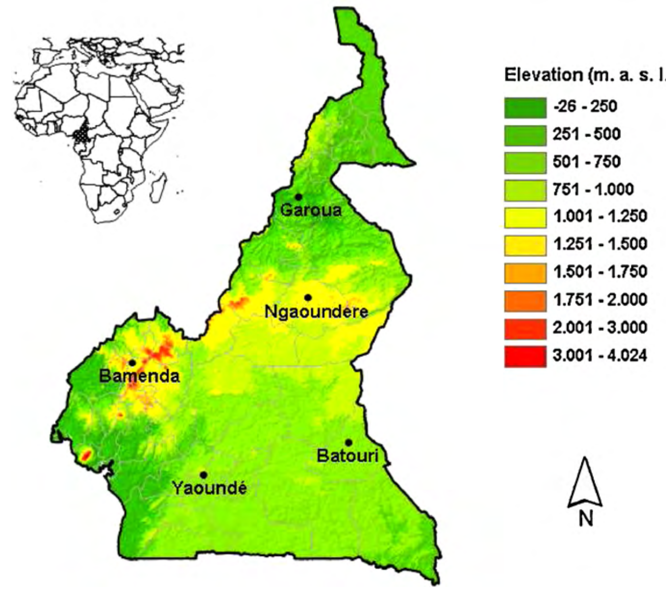

Fig. 1. Digital elevation model (DEM) of Cameroon and location of the five meteorological stations (Laux et al., 2009a).

The humid equatorial zone in the south favours the cultivation of cash crops, such as oil palm, bananas, cocoa, rubber, plantains, and coffee. There, the key food crops are maize *Zea mays* L., groundnut *Arachis hypogaea* L., sorghum *Sorghum bicolour* L., bambara groundnut *Vigna subterranean* L. Verdc, and soybean *Glycine max* L. Merr. The semi-arid region in the north favours the growth of millet, sorghum, maize, and groundnut (Tingem et al., 2008).

Representative soil properties (thickness and texture) for each of the simulation points were extracted from the International Soil Reference and Information Center database (www.isric.nl; Batjes, 1995). Data (e.g. yield, phenological parameters) were obtained from the district reports published by the Central Bureau of Statistics (Agristat, 2001).

Daily maximum temperature (T_{max}), minimum temperature (T_{min}), and rainfall data from 1979 to 2003 were obtained from the University Cooperation for Atmospheric Research (UCAR) (http://dss.ucar.edu/datasets). Five weather stations across Cameroon were chosen to represent different climatology (Table 1) and soil types. Solar radiation data, a key input in crop models, were not available. As solar radiation can be a major source of error in yield estimates (Rivington et al., 2005), solar radiation data were estimated using the empirical functions of *CropSyst* based on the air temperature data, ensuring that the uncertainties between the compared climate change scenarios remain constant.

2.2. Fuzzy logic-based ORS algorithm

The ORS determines the planting date which is calculated following the approach of Laux et al. (2008). Based on rainfall data alone, it was developed to estimate the optimal planting date for the Volta basin in West Africa, but it can be operationally adapted

Table 1
Location and mean climatological characteristics of five observation stations across Cameroon.

Station	Latitude (°E)	Longitude (°N)	Elevation (m a.s.l)	T_{min} (°C)	T_{max} (°C)	Rainfall (mm)
Bamenda	6.05	10.10	1239	14.8	24.6	2378
Batouri	4.47	14.37	656	18.9	28.9	1499
Garoua	9.33	13.38	244	22.7	33.1	1090
Ngaoundéré	7.34	13.57	1104	15.5	28.1	1514
Yaoundé	3.83	11.51	760	19.6	27.7	1655

to different climatic regions and different crop varieties via fuzzy logic. The ORS is calculated as the first day of the year where the product of three different membership grades

$$\mu = \mu_1\,\mu_2\,\mu_3 \tag{1}$$

exceeds a certain threshold, k. This ‘defuzzification’ threshold can range between 0 and 1.

The membership grades are calculated by means of membership functions accounting for rainfall amounts, number of rainy days, and the occurrence of dry spells. The membership functions can be described as a special form of triangular fuzzy numbers (subscript T), in which the third number is assigned to $+\infty$. The membership functions of the ORS algorithm of Laux et al. (2008) are illustrated in Fig. 2. The first membership function is described by the triangular fuzzy numbers $(18, 25, +\infty)_T$ and accounts for the *total rainfall amount within a 5-day spell*. The membership grade, μ_1, of rainfall amounts less than 18 mm is set to zero and amounts larger than 25 mm to unity. Between 18 and 25 mm of rainfall, the membership grade is interpolated linearly.

The second membership function describes the *number of wet days within a 5-day-spell* and is allowed to vary between 1 and 5. It can be described as $(1, 3, +\infty)_T$. The third function, the so-called *false start criterion* of the ORS algorithm, describes the *number of consecutive days after the ORS, in which no dry spell* $>$ *6 days occurs*. The respective fuzzy numbers are $(22, 30, +\infty)_T$.

The planting date is a function of seven parameters: the marginal values of the linearly interpolated parameter domain of the membership functions, a_1, a_2, b_1, b_2, c_1, and c_2 (see Fig. 2) and the ‘defuzzification’ threshold k. These parameters depend on the rainfall conditions at a particular location and the crop water requirement of different species. More information about the ORS algorithm is given in Laux et al. (2008).

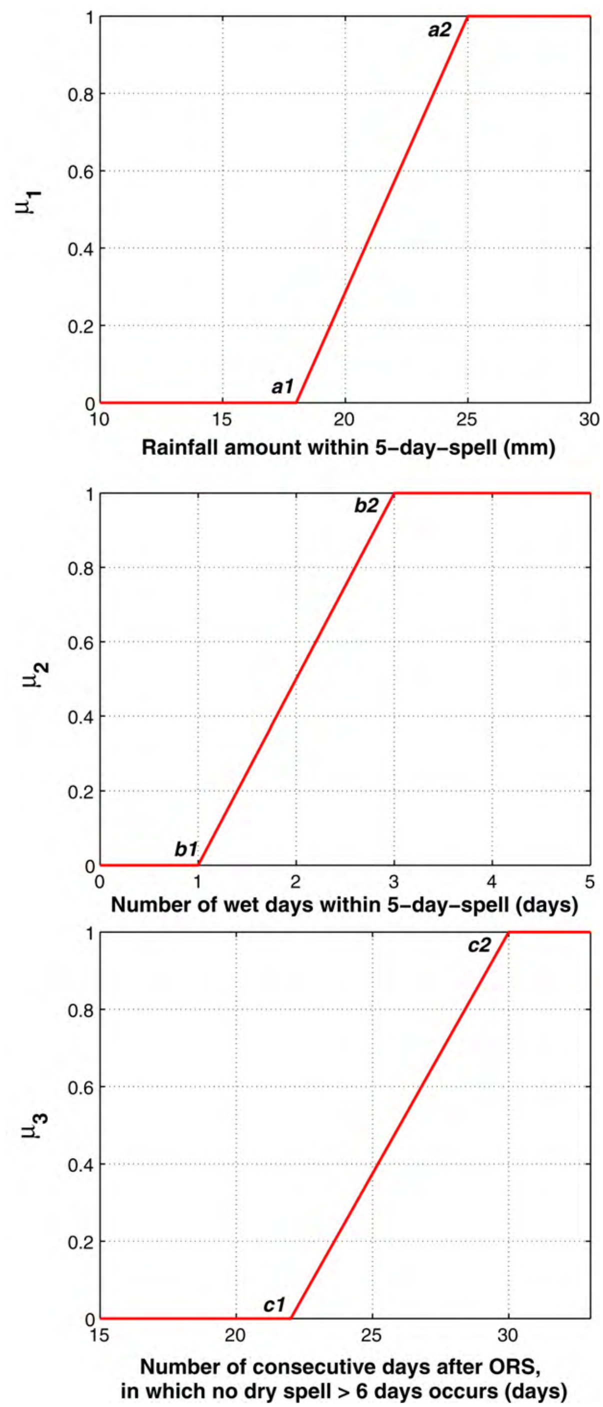

Fig. 2. Fuzzy logic membership functions for estimating the onset of the rainy season as applied, e.g. for the Volta basin of West Africa (Laux et al., 2008).

2.3. The CropSyst model

CropSyst is a multi-year, multi-crop, daily time step cropping systems simulation model developed for studying the effect of the interaction of climate, soils, and management on the productivity and environment of cropping systems (Stöckle et al., 2003). The model simulates the soil water budget, crop phenology, canopy and root growth, biomass production, crop yield, residue production and decomposition, soil erosion by water, and salinity. These processes are affected by weather, soil and crop characteristics, and cropping systems management, such as crop rotation, cultivar selection, irrigation, nitrogen fertilisation, soil and irrigation water salinity, tillage operations, and residue management. The required meteorological input data comprise maximum temperature (T_{max}), minimum temperature (T_{min}), rainfall and solar radiation on daily time scale.

The unstressed (potential) biomass growth is calculated as a function of crop intercepted photosynthetically active radiation (PAR) and potential transpiration. However, both the actual biomass growth, as well as the resulting crop yield, are limited by the stress intensity of water and nitrogen as expressed by the harvest index (Monteith, 1981; Tanner and Sinclair, 1983). The simulated crop yield is calculated as the ratio between the actual total biomass accumulated at physiological maturity and the crop-specific harvest index (harvestable yield/above ground biomass). Crop growth is dependent on the thermal time required to reach specific development stages, expressed as growing degree days (GDDs) accumulated throughout the growing season. GDDs are a function of daily maximum and minimum air temperatures and the crop base temperature.

Stress due to temperature and water reduces crop yield by accelerating the accumulation of thermal time (thereby reducing the GDDs). Stress sensitivity is allowed to differ between specific crops in the development stages in the model. In effect, crop yield can be seen as a complex integrator of weather over time (Katz et al., 2003).

The water budget is considered in the model via rainfall, runoff, infiltration with redistribution in the soil profile, and evapotranspiration (interception by crop canopy and residues, crop transpiration, soil evaporation). Soil water dynamics are calculated using Richards equation which is solved numerically using finite differences. More detailed information about *CropSyst* can be found in Stöckle et al. (2003).

The parameterisation of crop-specific values is performed based on the experience of Tingem et al. (2008) and on proposed values from the *CropSyst* user manual (Stöckle and Nelson, 2003). Further parameters are obtained by minimising the difference between observed and simulated crop yields. Phenological parameters (e.g. GDD) are calibrated using data provided by the Institute of Agricultural Research (IRA-Cameroon).

Fig. 3 shows the simulated vs. the observed crop yields for 2001–2003. The difference between modelled and observed yields lie within an acceptable range (Tingem et al., 2008, 2009).

For estimating the potential evaporation, the approach of Priestley and Taylor (1972) is applied using a Priestley–Taylor constant of 1.26 for Cameroon.

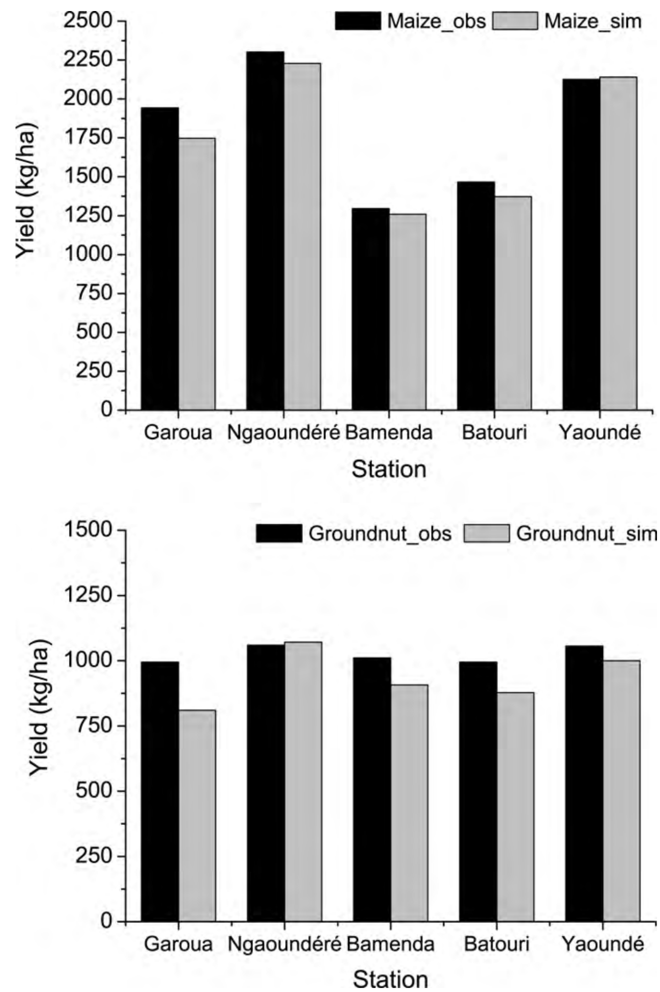

Fig. 3. Comparison of observed (black bars) and simulated yields (grey bars) for maize (top) and groundnut (bottom) for five stations in Cameroon and the period 2001–2003.

2.4. Optimal planting dates following the crop modelling system

In order to optimise the ORS algorithm of Laux et al. (2008) for the crop species of maize and groundnut and five different locations in Cameroon, a Monte Carlo approach was applied, in which the ORS algorithm was connected to the physically based crop model *CropSyst*. An objective function was used to identify the best parameter domain for the ORS algorithm to maximise the mean annual crop yield (MCY) for 1979–2003.

The optimisation procedure includes the following steps and is illustrated in Fig. 4:

Step 1: Initialise the ORS algorithm parameter domain for a_1, a_2, b_1, b_2, c_1, c_2, and 'defuzzification' threshold value k.
Step 2: Choose randomly seven parameters within the parameter domain.
Step 3: Calculate the ORS dates from 1979 to 2003 using the ORS algorithm and assigning the ORS dates as planting dates to *CropSyst*.
Step 4: Simulate the annual crop yield for the period 1979–2003 and calculate the performance parameter MCY.
Step 5: Repeat Step 2–Step 4 500 times and derive the parameter range of the best 5% simulations in terms of the MCY.
Step 6: Repeat Step 2–Step 5 with the new parameter domain obtained from Step 5 10 times and select the best parameter range of best iteration in terms of the MCY.

The initial values for the ORS algorithm parameter domain were set to vary within reasonable ranges (Table 2). A sensitivity analysis was performed to restrict the initial parameter range of k, expressed as boundary values k_1 and k_2, to 0.1 and 0.9 respectively, and thus, to save computation time (Laux et al., 2009a). Low values of k lead to early ORS dates with increasing risk of total crop failure, while high values reduce drastically the growing time (Laux et al., 2008).

2.5. Joint climate–crop–agricultural management modelling

The impact of climate change on agricultural productivity is analysed using adapted and traditional planting dates. This analysis is a continuation of the work of Tingem et al. (2008), Laux et al. (2008), and Laux et al. (2009a).

Climate change scenarios are generated for five locations in Cameroon, that represent different climatic conditions (Table 1). Therefore, large-scale A2- and B2-driven coupled atmosphere/ocean GCM (A-OGCM) temperature and precipitation time series on a daily time scale are statistically downscaled using a weather generator. A-OGCMs are suitable for creating climate change scenarios, as they estimate changes in climate due to increased CO_2 concentrations in a physically consistent matter (Alexandrov and Hoogenboom, 2000). The standard scenario generation methodology (ANL, 1994) is followed:

Table 2
Initial values for the parameter domain of the ORS algorithm (see Fig. 2).

a_1	a_2	b_1	b_2	c_1	c_2
10	30	1	5	5	40

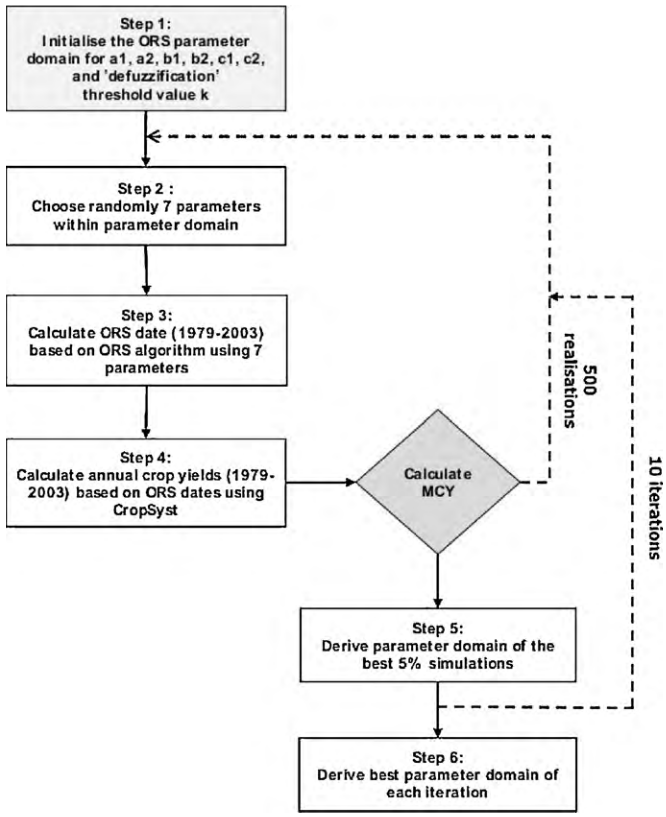

Fig. 4. Flowchart of applied optimisation approach.

- Atmospheric CO_2 concentrations are specified for the periods 2010–2039 (referred to as the 2020s) and 2070–2099 (referred to as the 2080s) according to the medium-high emission scenario A2 and its more optimistic medium–low counterpart B2 (Houghton et al., 2001) using the two A-OGCMs GISS (NASA/Goddard Institute) and HadCM3 (British Hadley Centre).
- Eight regional climate change scenarios are created by considering the difference of transient (successively changing boundary conditions) A-OGCM runs and the control run of current climate of the climatologically normal period (1961–1990). Temperature is adjusted by adding the change in temperature, while precipitation is adjusted by multiplying ratio changes in precipitation suggested by transient A-OGCM runs.
- For the climatologically normal period (extended baseline period), a CO_2 concentration of 330 ppm (350 ppm) is assumed.
- Based on the projected regional climate change signals and statistics of the observed precipitation and temperature data of the 1979–2003 baseline period, synthetic time series are simulated for the five locations in Cameroon using the stochastic weather generator *ClimGen*. ClimGen preserves the interdependence among the generated weather variables and their seasonal characteristics. Generated precipitation, T_{min}, and T_{max} values result from a continuous multivariate stochastic process with the daily means and standard deviations conditioned by the dry or wet state of the day. A first order Markov chain is used to calculate the probabilities for wet and dry days, as well as the transition probabilities. Based on the probabilities obtained, precipitation amounts are generated using a Weibull distribution and random numbers. More information about *ClimGen* and major differences with other weather generators like WGEN (e.g. Richardson, 1981; Richardson and Wright, 1984) are discussed in Stöckle et al. (2003).
- As long-term data are required to account for the probability of extreme events, the observed 25-year baseline was extended by another 'artificial' 25-year time series holding similar statistics as the observed baseline (hereinafter referred to as extended baseline period). Thereby, 50-year climatological time series are generated for each scenario and each location, representing the 2020s and the 2080s, thus providing a broad range of conditions that capture the variability and the range of uncertainties.

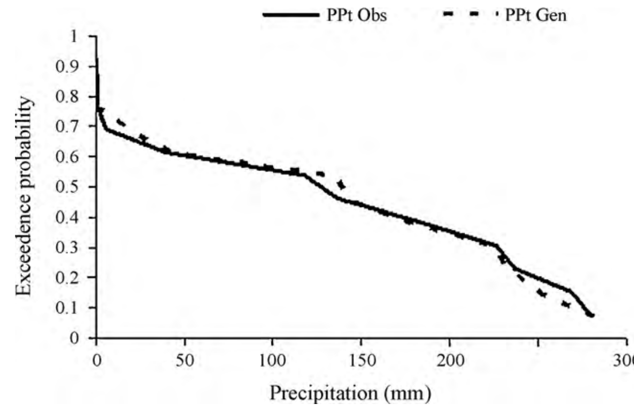

Fig. 5. Exceedance probability functions of observed and generated (*ClimGen*) monthly precipitation time series at station Ngaoundéré (Tingem et al., 2007).

Using statistical tests, no significant differences between time series of observed and simulated weather variables could be detected for different observation stations across Cameroon in terms of their mean values, variances, and distributions (Tingem et al., 2007). For example, Fig. 5 shows the exceedance probability functions for the distribution of monthly mean precipitation for the observed and generated *ClimGen* time series at station Ngaoundéré (Tingem et al., 2007). Observed and simulated probabilities are in good agreement.

In general, this procedure to generate the climate change scenarios on a local scale includes the following sources of uncertainties: (i) uncertainties in future emissions of greenhouse gases; (ii) uncertainties in converting emissions into greenhouse gas concentrations; (iii) uncertainties in converting concentration into radiative forcings; (iv) uncertainties in modelling the climate response to a given forcing; and (v) uncertainties in converting the model response into inputs for impact studies using downscaling techniques IPCC (2001).

Fig. 6 illustrates the procedure employed in this study: the generated time series are used as input for the crop model *CropSyst* to assess the impact of climate change. In order to quantify the potential effects of direct CO_2 fertilisation and changed management practices, the simulations are made (i) with and without direct CO_2 fertilisation effect, and (ii) with optimised and traditional planting dates. In order to save computation time, it is assumed that the optimal parameters for the ORS definition remain stationary in the 2020s and 2080s. The simulation results of the extended baseline period (1979–2003) and the 2020s and 2080s are compared. Indirect effects of increased CO_2 concentration on agricultural productivity are assessed by comparing the expected changes of precipitation, temperature, and solar radiation (e.g. Alexandrov and Hoogenboom, 2000).

3. Results

Section 3 is divided into two subsections 3.1 and 3.2, dealing with crop modelling results obtained for the observed baseline period (1979–2003) and the expected crop yields for the 2020s and 2080s, respectively.

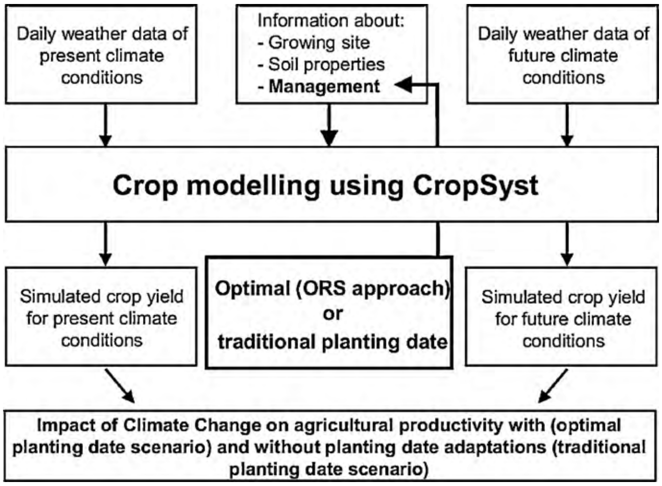

Fig. 6. Schematic illustration of the *joint climate–crop–agricultural management modelling system* applied to assess the impact of climate change for adapted and traditional planting dates.

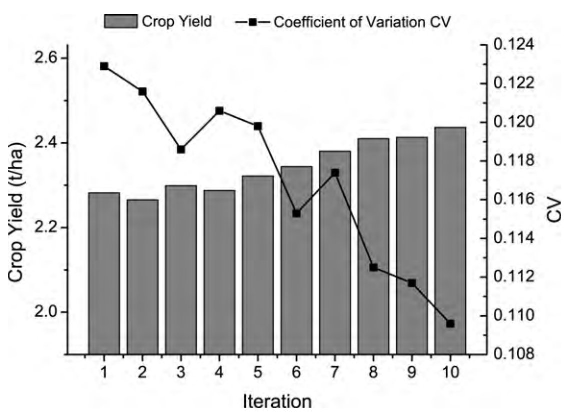

Fig. 7. Mean maize yield (1979–2003) per iteration at Yaoundé during the optimisation procedure (see Section 2.4).

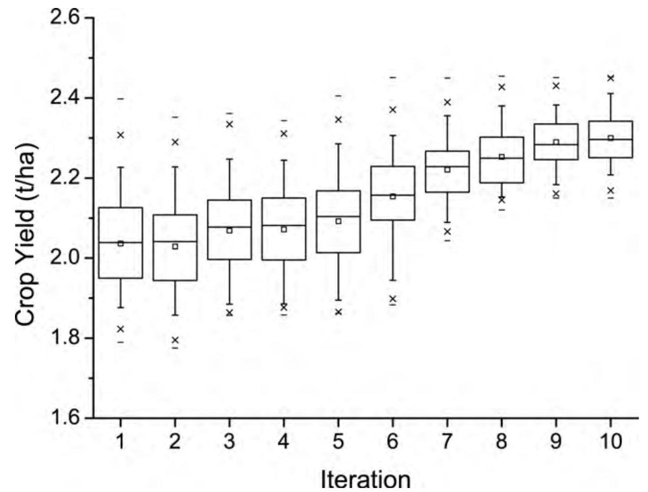

Fig. 8. Box–whiskers plot of simulated mean maize yield (1979–2003) at Yaoundé using 500 realisations per iteration of the optimisation procedure (see Section 2.4). The boxes have lines at the lower Q1 and upper quartile Q3 and the median values Q2 (middle horizontal lines). The whiskers (vertical lines) are lines extending from each end of the boxes to show the extent of the rest of the data. The maximum length of the whiskers is determined by 1.5 (Q3–Q1). Outliers (crosses) are data with values beyond the ends of the whiskers.

3.1. Crop yield modelling for the observed baseline period 1979–2003

3.1.1. Mean attainable crop yield and inter-annual analysis

The mean attainable maize yield and the mean coefficient of variation (CV, which is calculated as the ratio between the mean standard deviation and the mean crop yield) for the best 5% simulations of the ten optimisation iterations performed at the station Yaoundé are obvious from Fig. 7. Compared to the traditional planting rules, the optimised ORS approach leads to an increase of 14% at the station of Yaoundé. Simultaneously, the CV is decreased. Table 3 summarises the simulation results of the mean attainable crop yield of the five stations for maize and groundnut using traditional planting rules (Ndemah, 1999) and using the ORS algorithm (under initial and optimised conditions) of Laux et al. (2008). The mean attainable crop yield of maize was increased for all stations in Cameroon, ranging from 0.2% for station Bamenda in the western part of Cameroon to 55% for the northernmost station of Garoua. Intermediate increases of maize yield of approximately 13–14% are found for Ngaoundéré and Batouri. For groundnut, the mean attainable crop yield was increased by up to 49% for Yaoundé, 37% for Garoua, 19% for Batorui, and 8% for Ngaoundéré. For Bamenda, a decrease of 4% is calculated.

Fig. 8 illustrates the box–whiskers plot of maize yield during the optimisation for Yaoundé (see Section 2.4). Each iteration is represented by 500 realisations. The interquartile range which is a measure of the width of the distribution, decreases, while the median is enhanced progressively. This indicates that the optimisation works reasonably well.

The differences in simulated maize and groundnut yields using the optimised and traditional planting dates on the inter-annual scale are obvious from Fig. 9. Except for a few years with marginal

Table 3
Absolute difference AD (relative difference RD) between observed and simulated crop yield, mean attainable yield (MCY) and mean planting dates (PD) of maize and groundnut using traditional planting rules (TRAD), initial conditions for the ORS algorithm (INIT), and optimised conditions for the ORS algorithm (ORS).

Maize	AD (RD) (kg/ha) (%)	MCY_{TRAD} (kg/ha)	MCY_{INIT} (kg/ha)	MCY_{ORS} (kg/ha)	PD_{TRAD} (doy)	PD_{INIT} (doy)	PD_{ORS} (doy)
Garoua	194.8 (10)	1747	2475	2521	135	211	215
Ngaoundéré	−73.7 (3)	2229	2454	2502	135	162	168
Bamenda	36.8 (3)	1259	1169	1261	75	108	72
Batouri	92.7 (6)	1373	1474	1561	75	169	171
Yaoundé	−14.3 (1)	2141	2282	2437	75	65	51
Groundnut							
Garoua	184.4 (19)	810	1100	1112	135	211	214
Ngaoundéré	−11.3 (−1)	1071	1162	1152	135	144	137
Bamenda	104.4 (10)	907	826	872	75	91	75
Batouri	116.5 (12)	878	998	1041	75	164	176
Yaoundé	55.93 (5)	1000	1431	1485	75	158	177

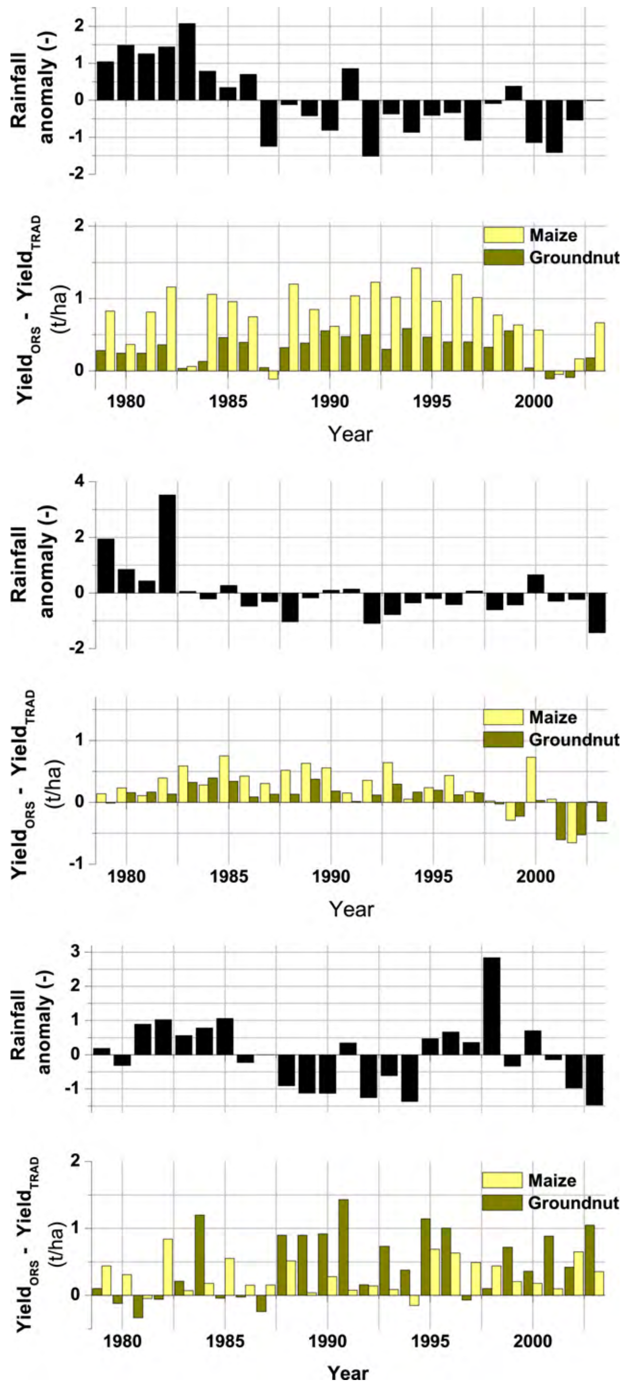

Fig. 9. Annual rainfall anomalies and differences in simulated annual maize (yellow bars) and groundnut yields (green bars) using traditional (TRAD) and optimised planting dates (ORS) for the observed baseline period (1979–2003) at Garoua (top), Ngaoundéré (middle), and Yaoundé (bottom). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

decreases, crop yield can be increased for most of the years. The ORS algorithm allows for crop yield increases in anomalous dry years.

3.1.2. Derived planting rules and planting date statistics

During the optimisation of the ORS approach using the *optimal planting date following crop modelling system* (see Section 2.4), the initial parameter domain of the ORS approach (see Table 2) is restricted for each station and cultivar, respectively. In this way, a station and cultivar based optimal (in terms of maximal mean crop yield) set of fuzzy rules, represented by fuzzy numbers, is obtained. Table 4 summarises the results of the optimisation. The differences in the fuzzy numbers between the different stations and cultivars are clearly visible. Maize, for instance, seems to be less vulnerable to dry spells within the first weeks after planting than groundnut. For the northernmost and arid stations of Garoua and Ngaoundéré, higher initial rainfall amounts represented by the fuzzy number a_1, than in the southern regions of Cameroon are required. The criterion *number of rainy days* represented by the parameters b_1 and b_2 could not be reduced remarkably.

Table 3 presents the planting date statistics following traditional planting rules with fixed planting dates (Ndemah, 1999) and rainfall-dependent planting rules according to the ORS algorithm of Laux et al. (2008). A relatively strong deviation of more than three months can be observed between the traditional and the optimised planting dates. The ORS algorithm leads to later planting dates, except for Yaoundé and Bamenda (maize).

3.2. Future crop yield estimations for the 2020s and 2080s

The analysis of climate change scenarios for five stations across Cameroon shows that temperature increases are of similar magnitude both for the HadCM3 and the GISS A-OGCMs, with slightly higher values for the GISS A-OGCM (Fig. 10). For the 2080s and the pessimistic scenario A2, a mean temperature increase of up to 4.9 °C is predicted for the station of Garoua. The daily $T_{max} > 30$ °C during the growing season is found to

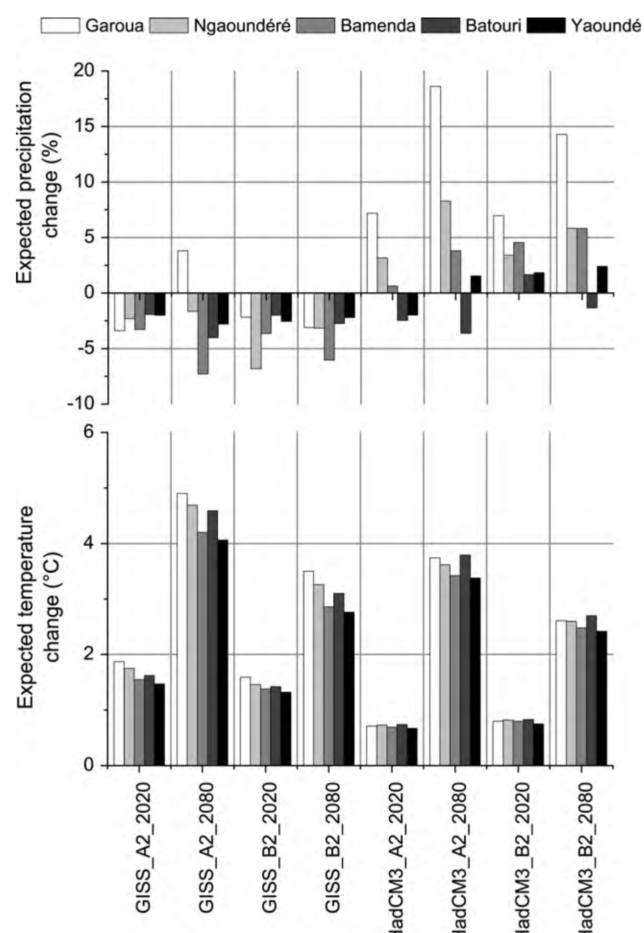

Fig. 10. Downscaled precipitation and temperature changes (compared to the extended baseline period) for the 2020s and the 2080s at five selected stations in Cameroon.

Table 4
Optimised criteria for estimating the planting date of maize and groundnut according to the ORS algorithm of Laux et al. (2008) (see Section 2.2).

Maize	μ_1		μ_2		μ_3		k		MCY (kg/ha)
	a_1	a_2	b_1	b_2	c_1	c_2	k_1	k_2	
Garoua	19	29	1	5	13	26	0.46	0.81	2521
Ngaoundéré	22	30	2	5	13	34	0.45	0.76	2502
Bamenda	12	29	1	4	5	22	0.03	0.49	1261
Batouri	12	25	3	5	7	25	0.42	0.69	1561
Yaoundé	10	26	1	2	6	18	0.13	0.41	2437
Groundnut									
Garoua	15	28	1	5	11	29	0.37	0.70	1112
Ngaoundéré	12	27	1	5	7	35	0.35	0.74	1152
Bamenda	10	27	1	3	5	16	0.19	0.59	873
Batouri	11	27	3	5	7	23	0.37	0.75	1041
Yaoundé	14	24	3	5	6	24	0.36	0.74	1485

increase for all climate change scenarios with higher occurrences for the 2080s compared to the 2020s, and with higher occurrences for the A2 compared with the B2 scenarios. Both A-OGCMs show the greatest increases at the stations of Garoua, Batouri and Yaoundé.

For rainfall, remarkable differences between HadCM3 and the GISS A-OGCM are observed (Fig. 10). While GISS produces mainly precipitation decreases for all stations for the 2020s and 2080s ranging from +3% to −8%, the situation is reversed for the HadCM3 scenarios. Precipitation is expected to range from −3% to +7% for the 2020s and from −5% to +18% for the 2080s. The differences are more pronounced at Garoua, Ngaoundéré, and Bamenda, while only weak differences are expected at Batouri and Yaoundé.

The impact of climate change on crop productivity in Cameroon is analysed based on the eight derived climate change scenarios (see Section 2.5 for further details). Changes in crop yield are expected to be mainly due to the direct CO_2 fertilisation effect and the indirect effects of expected rainfall and temperature changes.

Fig. 11 shows the simulated maize and groundnut yields considering the direct CO_2 fertilisation effect, its indirect effects on rainfall and temperature, and adapted planting rules for all five stations.

According to the simulation results, climate change could be advantageous for the groundnut yield in the 2020s and 2080s, with yield surpluses of about 30% for the 2020s compared to the extended baseline period. The stations of Bamenda and Yaoundé show a decrease in yields for most scenarios. For maize, crop yield is expected to increase (decrease) for the 2020s (2080s) by about 15%.

The impact of planting date adaptations on future attainable crop yield is depicted in Fig. 12. For Garoua and Batouri, the attain-

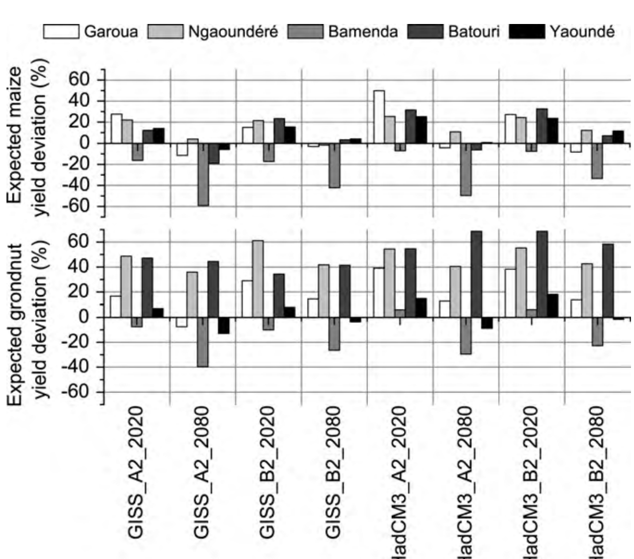

Fig. 11. Simulated crop yield considering the direct CO_2 fertilisation effect, its indirect effects on rainfall and temperature, and adapted planting rules for five selected stations in Cameroon.

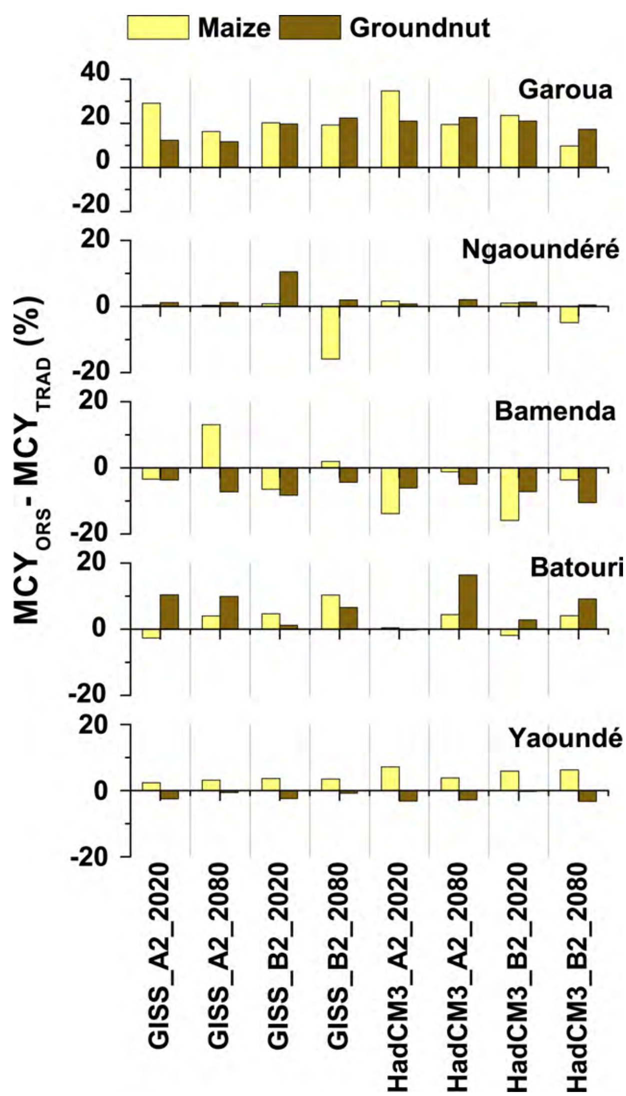

Fig. 12. Deviation (%) between the simulated mean annual crop yield (MCY) using optimised (ORS) and traditional planting dates (TRAD) for different climate change scenarios (2020s and 2080s).

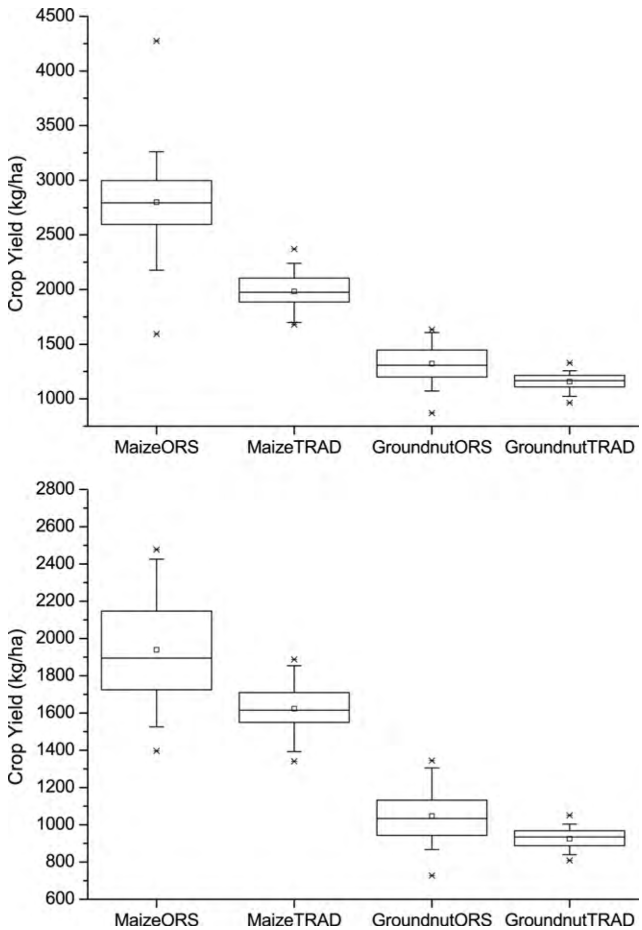

Fig. 13. Box–whiskers plot of simulated mean maize yields for the 2020s (top) and 2080s (bottom) at Garoua using the downscaled weather files from the A2-driven GISS A-OGCM model and traditional and optimised planting rules. The boxes have lines at the lower Q1 and upper quartile Q3 and the median values Q2 (middle horizontal lines). The whiskers (vertical lines) are lines extending from each end of the boxes to show the extent of the rest of the data. The maximum length of the whiskers is determined by 1.5 (Q3–Q1). Outliers (crosses) are data with values beyond the ends of the whiskers.

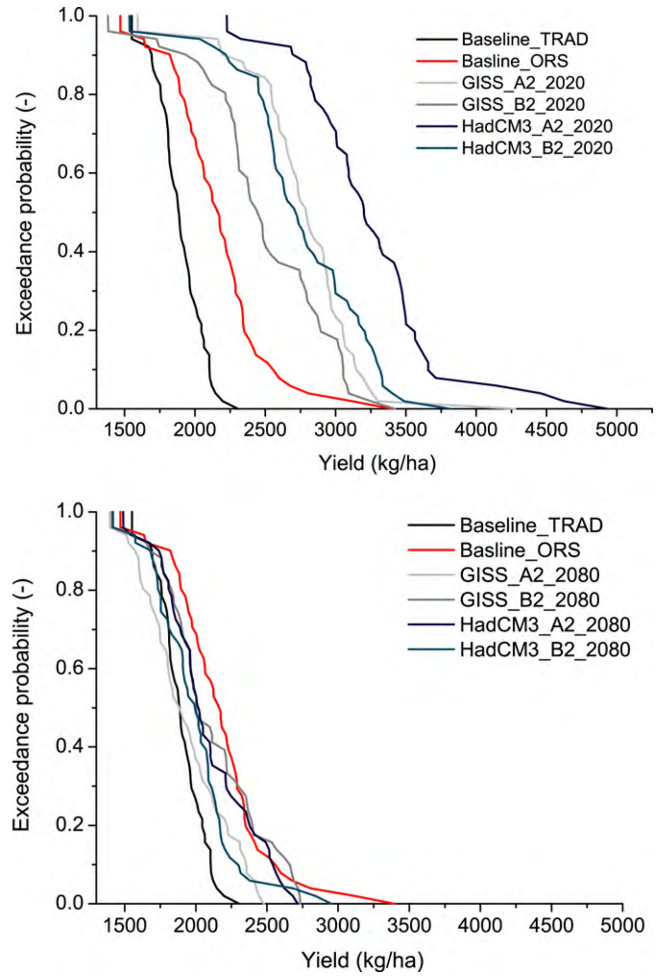

Fig. 14. Exceedance probability of the maize yield (kg/ha) at Garoua for the extended baseline period using traditional (TRAD) and optimised (ORS) planting rules and different climate change scenarios with optimised planting rules for the 2020s (top) and 2080s (bottom).

able mean annual crop yield (MCY) was mostly increased for maize and groundnut when using the ORS algorithm. For Yaoundé, only maize yields benefited from the algorithm, and for Ngaoundéré, the simulations did not indicate any benefit. For Bamenda, predominantly negative responses are expected.

Fig. 13 compares the simulated mean crop yields for the 2020s and 2080s at Garoua using optimised planting rules according to simulation results using traditional planting rules. In both cases, the distributions of the mean yields using optimised planting rules are broader than the results using the traditional planting dates.

Garoua was found to be the station with the highest potential of future crop yield increase for maize and groundnut. Apart from the mean annual crop yield results, Fig. 14 shows the exceedance probability of the maize yield (kg/ha) at Garoua for the extended baseline period using traditional and optimised planting rules and different climate change scenarios for the 2020s and 2080s. Following the ORS algorithm with optimised planting rules, the exceedance probability of the simulated maize yield increases during the 2020s compared with the extended baseline period. For the 2080s, however, the probability drops below the baseline level of the optimised planting rules, but still exceeds the level of the traditional planting rules.

Fig. 15 shows the exceedance probability of the modelled growing season's length of maize for the extended baseline period as well as for the derived climate change scenarios (2020s and 2080s) at the five stations in Cameroon. The length of the growing season is calculated as the difference in days between maturity date and planting date. The higher temperatures that are expected due to climate change, accelerate the phenology of plants and generally result in earlier maturation. The shortened growth cycle, in turn, may reduce the yield potential of annual crops (Rosenzweig and Hillel, 1998). The growing cycle of optimised planting dates is extended in relation to the traditional planting rules and great reductions of its length are calculated for the 2080s compared to the baseline period. Growing periods are shorter under GISS scenarios than under HadCM3, because the projected temperature increase under HadCM3 is more moderate compared to GISS.

Fig. 16 illustrates the impact of climate change as a combined signal of precipitation, temperature, and atmospheric CO_2 change as well as the impact of atmospheric CO_2 change on the maize yield at Garoua with traditional and adapted planting dates. The simulation results obtained are compared to the extended 50-year baseline period.

It is found that atmospheric CO_2 fertilisation, induced by the A2 and B2 scenario, generally increases the maize yield for the 2020s and 2080s. For the 2020s, crop yield can be increased approximately by 10%, and for the 2080s, a gain of 30% can be obtained. As far as the

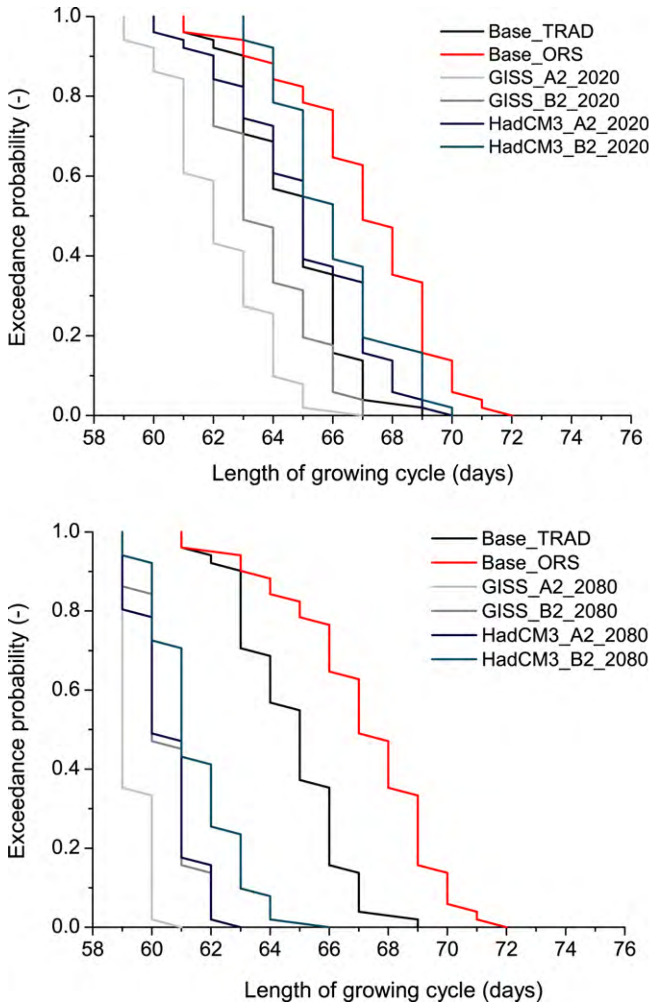

Fig. 15. Exceedance probability of the length of the growing cycle of maize (days) at Garoua for the extended baseline period using traditional (TRAD) and optimised (ORS) planting rules and different climate change scenarios with optimised planting rules for the 2020s (top) and 2080s (bottom).

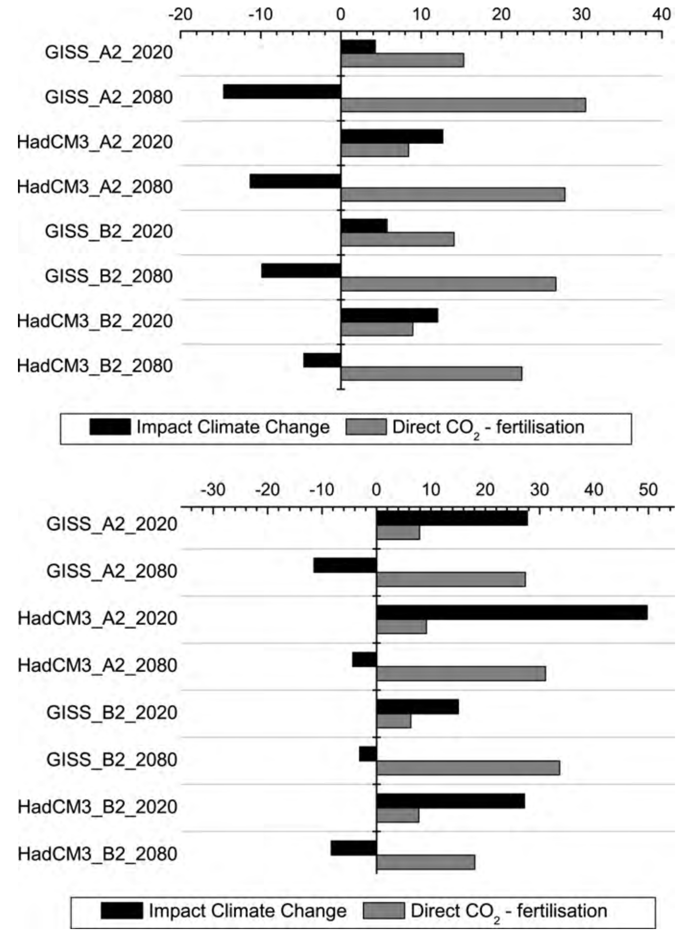

Fig. 16. Impact of climate change (precipitation, temperature, direct CO_2 fertilisation) and of direct CO_2 fertilisation exclusively on maize yield (%) at Garoua when using traditional (top) and adapted planting dates (bottom).

total effect of climate change is concerned, however, crop yield is expected to increase slightly for the 2020s due to the temperature increase and to drop drastically in the 2080s. Using adapted planting dates, crop yield can be increased significantly for the 2020s compared with the traditional planting dates. The negative effects for the 2080s are mitigated by adapted planting rules.

For groundnut as a representative of C3 plants, the expected direct fertilisation effects are not as high as those for maize (C4 plant). In contrast to maize, the net effect of climate change (including any enhanced CO_2 fertilisation effect) is expected to consistently improve groundnut yields (Fig. 17). The 'optimal planting date scenario' results in higher crop yield increases than the 'traditional planting date scenario', except for the GISS A2 scenario.

4. Discussion

Instead of using a fixed definition parameterisation for national or transnational ORS predictions (e.g. Raes et al., 2004; Laux et al., 2008; Mugalavai et al., 2008; Kniveton et al., 2009; Marteau et al., 2009), it was demonstrated that crop productivity was significantly increased under local weather conditions. This is in agreement with conclusions of Alexandrov and Hoogenboom (2000) and calls for an estimation of these parameters on a local rather than on a regional scale. It could therefore be shown that optimally defined parameters differ between the various stations and cultivars.

The simulated mean planting dates based on the intra-seasonal rainfall variability can strongly deviate from the traditional planting dates as proposed by Ndemah (1999) for Cameroon during the baseline period. For Garoua, the optimal planting date deviates by more than two months from the traditional dates for maize and groundnut. For Yaoundé, maize should be planted earlier than the traditional planting date, and on the contrary, the optimal planting date for groundnut is found to be delayed by about three months at the beginning of the second rainy season. For climate change projections, relatively small differences in ORS distributions are observed between the two time periods and the two emission scenarios. The differences are greatest between the two different A-OGCMs (not shown here). For Garoua, the median of ORS dates differs by about 10 days between the A-OGCMs for the 2020s, while differences are smaller for the 2080s. In general, it is found that differences (uncertainties) in ORS date distribution between the A-OGCMs are greater than those between the emission scenarios and the two time periods. The *optimal planting date following crop modelling system* leads to a decreasing interquartile range of the attainable crop yields for the baseline period. For station Bamenda, however, this approach is not useful, as temperature and not water availability is the dominant limiting factor for agricultural productivity in this mountainous region.

The expected increase in temperature is expected to reduce the growing cycle. This generally leads to a decreasing crop productivity (Alexandrov and Hoogenboom, 2000). However, the positive

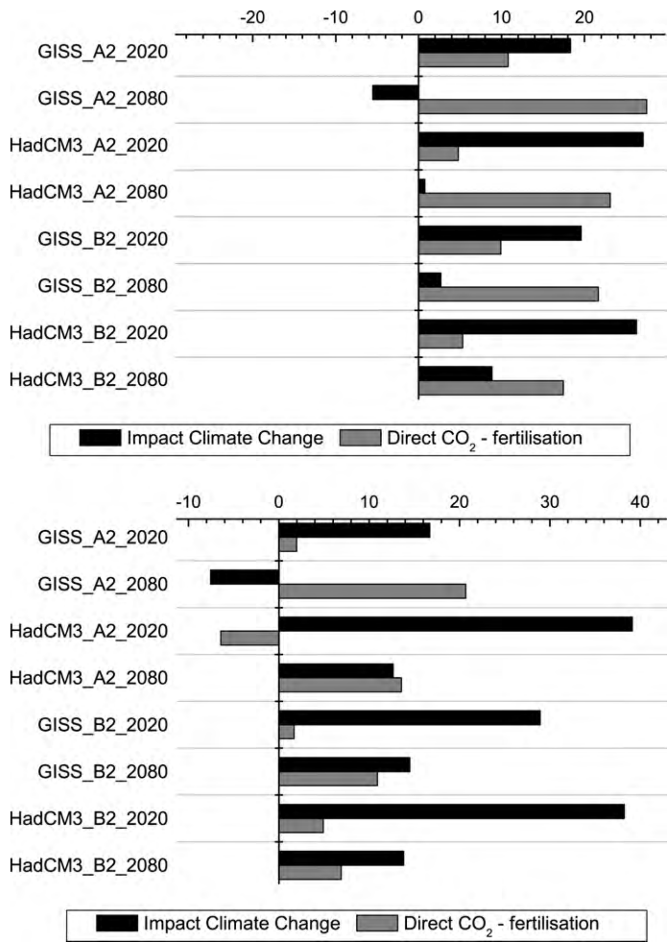

Fig. 17. Impact of climate change (precipitation, temperature, direct CO_2 fertilisation) and of direct CO_2 fertilisation exclusively on groundnut yield (%) at Garoua for traditional (top) and adapted planting dates (bottom).

effect of direct CO_2 fertilisation outweighs the negative effects of precipitation and temperature change. Simulations excluding the effect of direct CO_2 fertilisation (not explicitly shown here), but accounting for future precipitation and temperature changes, lead to yield declines of approximately 15% for the 2020s and 25% for the 2080s for maize and of 25% for the 2020s and 30% for the 2080s for groundnut. This partly contradicts the conclusion of Nakicenovic and Swart (2000), who state that the direct fertilisation effect of CO_2 cannot be expected to be significant before 2050. Theoretical assumptions were confirmed, according to which the direct fertilisation effect of CO_2 is of greater importance to C3 plants represented by groundnut than to C4 plants represented by maize, because these crops are already near their maximum photosynthesis rate under the current level of atmospheric CO_2 (e.g. Hörmann and Chmielewski, 1998). When exceeding the maximum net photosynthetic rates, solely negative impacts are expected due to increasing negative indirect effects on crop yield.

5. Summary and conclusions

Especially for rainfed regions such as Cameroon, the inherent variability of weather, i.e. the intra-seasonal and inter-annual rainfall variability, but also imperfect agricultural management decisions often prevent crop yields from reaching their full potential. Of all agricultural management decisions, the decision on the planting date, roughly going along with the start of the rains, is of utmost importance. The estimation of agriculturally optimal planting dates is not a trivial task, since dry spells which often occur after the onset of rain could have drastic consequences for crop productivity and even result in total crop failures.

The study presented here was therefore focussed on i) developing an approach to supporting decisions on the optimal planting date for five stations in Cameroon, and (ii) assessing the climate change impacts on crop productivity and, thus, food security in Cameroon. For this reason, a method using an *optimal planting date following crop modelling system* was presented and evaluated with intra-annual rainfall variability being taken into account.

Using the *optimal planting date following crop modelling system*, optimal planting rules in terms of fuzzy numbers were derived for five stations in Cameroon. Physically based crop models, such as *CropSyst*, are appropriate tools for the derivation of optimal planting rules depending on the local weather conditions. Depending on (changed) temperature, rainfall and solar radiation values, CropSyst simulates measures such as soil water budget, crop phenology, canopy and root growth, biomass production, and crop yield, which in turn affect the optimal planting rules in terms of fuzzy numbers. Optimal planting rules obtained differ between the cultivars (here, maize and groundnut) and various stations across Cameroon. For the northernmost and driest stations of Garoua and Ngaoundéré, the *total rainfall amount within a 5-day spell* at the beginning of planting (first ORS membership function) differs remarkably compared with wetter stations. In general, it is found that the ORS criterion 1 and the *number of consecutive days after the ORS, in which no dry spell* $>$ *6 days occurs* (third ORS membership function) are more important than the *number of wet days within a 5-day-spell* at the beginning of planting (second ORS membership function).

Using the optimised planting rules in terms of maximal mean crop yields (1979–2003), the mean attainable crop yield was increased significantly under current and future climate conditions and its inter-annual variability was decreased significantly compared to simulations for traditional planting rules. Instead of maximising the mean crop yield as an objective function, the coefficient of variation could be used. This would be of benefit to subsistence farmers, who are more interested in relatively good yields in poor rainfall years than in good average years (Brouwer et al., 1993).

According to the crop yield modelling results based on climate change scenarios, small increases in crop productivity for the 2020s, but drastic declines for the 2080s are expected for Cameroon, especially for the A2 scenarios. Farming management decisions on the planting date were included in the simulations by a *joint climate–crop–agricultural management modelling system* (see Section 2.5). Under the assumption of stationarity of optimised planting rules derived from the baseline period, future crop yields were estimated and analysed. Improving farming management, referred to as the 'optimal planting date scenario', could help mitigate the expected negative impacts of climate change. The northern regions, represented by the stations of Garoua and Batouri would benefit most from planting date adaptations. It is expected that the ORS algorithm is particularly valuable for regions where crop water availability predominantly falls below crop evaporative demand (depending on crop type, variety and development stage) and thus can be seen as major factor limiting crop growth. For the other stations analysed, the use of the ORS algorithm shows no significant improvement for the 2020s and 2080s compared to traditional planting rules. Inherent uncertainties associated with A-OGCMs, and consequently, the resulting (optimal) ORS dates are found to exceed uncertainties in different emission scenarios and time periods.

The algorithm developed to estimate the optimal planting date might be potentially useful for agricultural decision making in Cameroon and other sub-Saharan countries. As it is fully operational, it can be adapted easily to other regions and cultivars of interest. For predicting the onset of the oncoming rainy season, however, the forecast skill for that region of interest must be analysed prior to application.

Adapting the planting date is a very cost-efficient way to potentially increase crop productivity and stabilise or even increase food security in rainfed regions which are most vulnerable to climate change. Ultimately, the ability of farmers to adapt effectively can affect regional and national economies which are highly dependent on agricultural production. However, farming management adaptations should only be considered as one important puzzle piece towards increasing food security. It should not be a substitute for other actions, such as the development of pest- and drought-resistant crops and high-yield varieties with shortened life cycles. Additional factors of farming management adaptations to climate change, such as changes in the cultivars, practices of cultivation, irrigation, pest control, etc. were not considered in this study.

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