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LETTER

Errors and uncertainties introduced by a regional climate model in climate impact assessments: example of crop yield simulations in West Africa

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Abstract

The challenge of estimating the potential impacts of climate change has led to an increasing use of dynamical downscaling to produce fine spatial-scale climate projections for impact assessments. In this work, we analyze if and to what extent the bias in the simulated crop yield can be reduced by using the Weather Research and Forecasting (WRF) regional climate model to downscale ERA-Interim (European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis) rainfall and radiation data. Then, we evaluate the uncertainties resulting from both the choice of the physical parameterizations of the WRF model and its internal variability. Impact assessments were performed at two sites in Sub-Saharan Africa and by using two crop models to simulate Niger pearl millet and Benin maize yields. We find that the use of the WRF model to downscale ERA-Interim climate data generally reduces the bias in the simulated crop yield, yet this reduction in bias strongly depends on the choices in the model setup. Among the physical parameterizations considered, we show that the choice of the land surface model (LSM) is of primary importance. When there is no coupling with a LSM, or when the LSM is too simplistic, the simulated precipitation and then the simulated yield are null, or respectively very low; therefore, coupling with a LSM is necessary. The convective scheme is the second most influential scheme for yield simulation, followed by the shortwave radiation scheme. The uncertainties related to the internal variability of the WRF model are also significant and reach up to 30% of the simulated yields. These results suggest that regional models need to be used more carefully in order to improve the reliability of impact assessments.

1. Introduction

The assessment of climate change impact on crop production is crucial to support adaptation strategies that ensure food security in a warmer climate. To evaluate these impacts, three modeling approaches are adopted: process-based models (e.g. EPIC (Williams 1990), SARRA-H (Dingkuhn *et al* 2003), DSSAT models (Jones *et al* 2003), APSIM (Keating *et al* 2003)), agro-ecosystem models (e.g. LPJmL (Bondeau *et al* 2007), ORCHIDEE (Krinner *et al* 2005), PEGASUS (Deryng *et al* 2011)), and statistical analyzes of historical data (e.g. Lobell and Burke 2010, Shi *et al* 2013). The goal of all these modeling approaches is to estimate crop productivity as a response to climate variability. Process-based models represent the physiological processes of crop development as a response to climate forcing. This approach is often preferred since it can be used to capture the complex effects of the climate, CO_2 concentration and management on crop productivity (Roudier *et al* 2011). However, the use of projected climate data from global climate models (GCM) to force crop models is challenging. The scale of the GCM grid points is much larger than the processes governing the yields at the plot scale (Baron *et al* 2005) and many agricultural models require input data that describes the environmental conditions at high spatial and temporal resolution. Thus, integrated climate–crop modeling systems need to appropriately handle the loss of variability caused by differences between the scales (Oettli *et al* 2011, Glotter *et al* 2014). This can potentially be achieved by downscaling GCM outputs. Dynamical downscaling offers a self-consistent approach that captures fine-scale topographic features and coastal boundaries by using regional climate models (RCMs) with a fine resolution (approximately 10–50 km) nested in the GCM (Paeth *et al* 2011, Glotter *et al* 2014). Although it can improve weather and climate variability (Feser *et al* 2011, Gutmann *et al* 2012) as well as crop yield projections (e.g. Mearns *et al* 1999, Mearns *et al* 2001, Adams *et al* 2003, Tsvetsinskaya *et al* 2003), dynamical downscaling is also an additional source of errors and uncertainties to crop yield projections. For example, when different RCMs were used to downscale atmospheric re-analyses to force the SARRA-H crop model in Senegal, Oettli *et al* (2011), large differences were found in the simulated sorghum yields depending on the RCM used. Moreover, these authors showed that a change in the physical parameterizations of a single RCM can lead to major changes in the derived crop yields. More recently, using two RCMs and the DSSAT-CERES-maize crop model over the United States, Glotter *et al* (2014) showed that although the RCMs correct some GCM biases related to fine-scale geographic features, the use of a RCM cannot compensate for broad-scale systematic errors that dominate the errors for simulated maize yields.

Projected yields rely on the accuracy of climate input data and are thus sensitive to the downscaling method. It is therefore crucial to quantify the errors inevitably propagated by such downscaling techniques through combined climate–crop modeling. However, to our knowledge, very few studies have investigated the sensitivity of local climate and the resulting simulated crop yields to choices in the experimental setup of a single RCM even though they can considerably affect the RCM output. For instance, RCMs are highly sensitive to the size and location of the domain (e.g. Seth and Giorgi 1998, Leduc and Laprise 2009), the lateral boundary conditions (e.g. Diaconescu *et al* 2007, Sylla *et al* 2009), the model's horizontal and vertical resolutions (e.g. Iorio *et al* 2004) and its physical parameterizations (e.g. Jankov *et al* 2005, Flaounas *et al* 2010, Crétat *et al* 2011b). Moreover, atmosphere and surface-atmosphere feedback processes are chaotic and result in an internal variability of the RCMs that is not reproducible (e.g. by a multimember ensemble simulation) (Crétat *et al* 2011a).

Here, we investigate the effect of using a RCM on simulated yields in Sub-Saharan Africa, one of the most vulnerable areas to climate change. We document and rank the errors and uncertainties arising from the physical parameterization and internal variability of the RCM. The chosen physical parameterizations of the regional Weather Research and Forecasting (WRF) model (Skamarock *et al* 2008) are systematically sampled to produce a set of downscaled ERA-Interim rainfall and incoming solar radiation time series at two sites in Benin and Niger. These climate variables are used to simulate Niger pearl millet and Benin maize yields with both the EPIC and SARRA-H crop models in order to evaluate (i) the effect of using the WRF on the simulated yield bias and (ii) the uncertainties arising from the choice of the physical parameterization. Sampling from among the different parameterizations also allows the selection of a satisfactory set of parameterizations for the WRF model for impact studies in Soudano–Sahelian Africa. This retained configuration is later used in this study to perform a 10-member ensemble simulation to assess the uncertainties linked to the internal variability of the WRF model.

The next section introduces the climate data, crop model, RCM and simulation protocols. Simulated crop yields using both raw ERA-Interim and WRF downscaled climate data are first compared. After highlighting the influence of the climate variables taken into account in the simulated yields, the impact of each physical parameterization on the simulated climate variables and yields is investigated. Finally, the uncertainties in the simulated crop yields induced by the internal variability of WRF are quantified.

2. Materials and methods

2.1. Location of the sites

Two sites of approximately one squared-degree (figure 1) are retained for this study; they are characterized by a rain-fed agriculture with low input on poor soils. The Niger site (orange box) is typical of Central Sahel conditions. There, the rainy season lasts approximately from June to September and provides roughly 450–600 mm of rainfall. The Benin site (yellow box) is in the Sudanian zone. There, the rainy season lasts up to six months from May to October providing 1200–1300 mm of rainfall per year.

2.2. Climate data

For each site, the observed meteorological data are taken from the AMMA-CATCH observation system (African Monsoon Multidisciplinary Analysis—Coupling the Tropical Atmosphere and the Hydrological Cycle; www.amma-catch.org). The precipitation is interpolated by kriging over each site using more than 50 rain-gauge measurements for the 2003–2009 period (for a detailed description of the method used, see Kirstetter *et al* 2013) while the other variables (radiation, temperature, relative humidity and wind) are

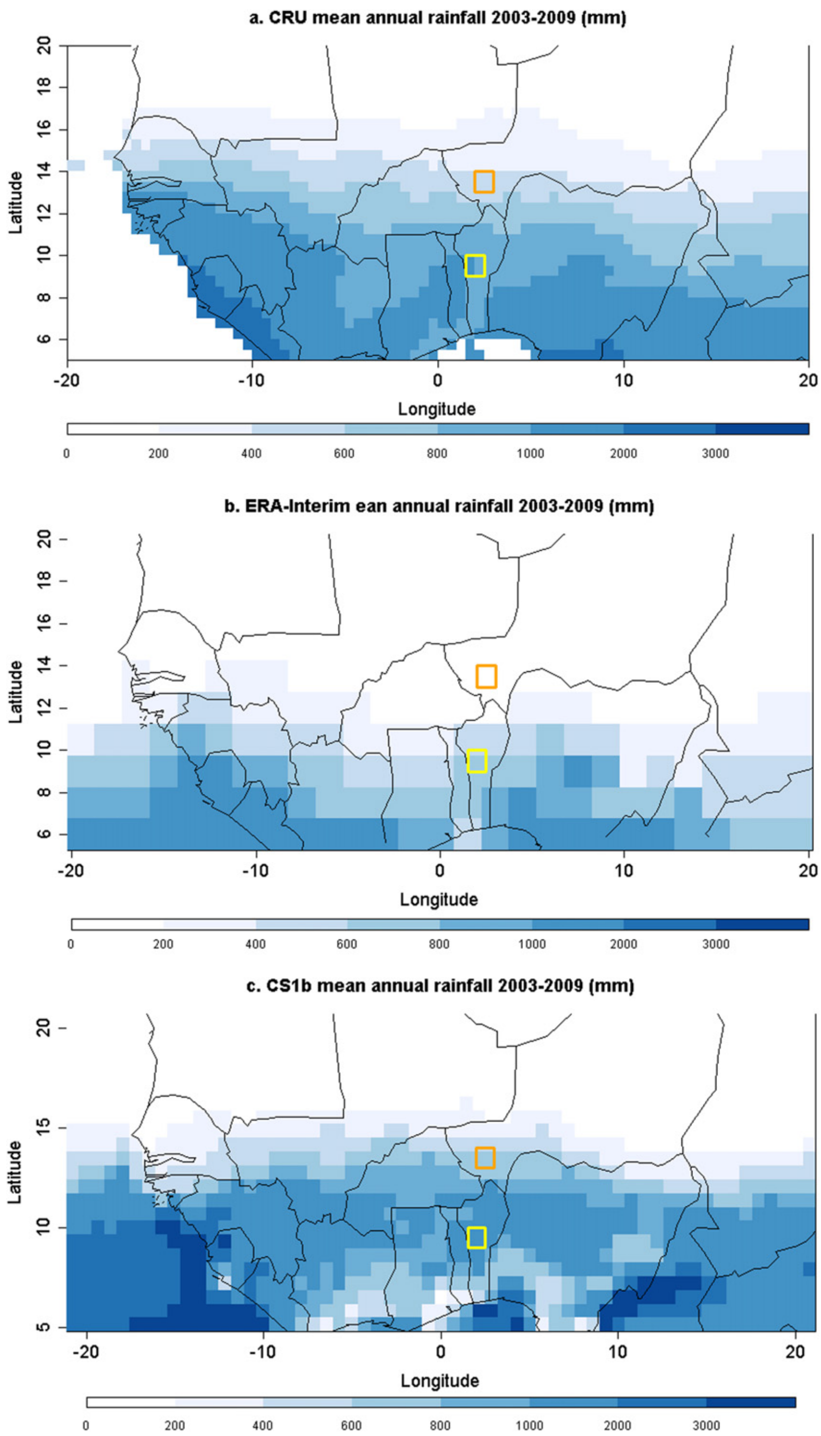

Figure 1. Map of West Africa and location of the sites. Mean annual rainfall (mm) averaged over the 2003–2009 period from (a) Climatic Research Unit (CRU) data, (b) ERA-Interim data and (c) a single physical configuration of the WRF model. The site in Niger in shown in orange and the site in Benin in yellow. The reference rainfall, from AMMA-CATCH OS and only available on these two sites, match the CRU data in Niger with an annual rainfall of 522 mm and the CS1b data in Benin with an annual rainfall of 1289 mm (table 2).

taken from synoptic stations. These data are considered as reference climate data and they are used to simulate the reference yields.

The ERA-Interim dataset (ERA-I; Simmons *et al* 2007, Dee *et al* 2011) consists of a set of global gridded analyses describing the state of the atmosphere, land and ocean wave conditions from 1979 to date. Climate variables from this dataset are used at a resolution of 1.5° to force the (i) WRF and (ii) crop models.

2.3. Climate downscaling experimental setup

All of the climate downscaling experiments are performed using the non-hydrostatic Advanced Research WRF ARW/WRF model, version 3.3.1 (WRF; Skamarock *et al* 2008). This model has been used in a large number of studies, some of which focus on West Africa (e.g. Vigaud *et al* 2009, Flaounas *et al* 2010, Klein *et al* 2015), and includes a large choice of physical schemes. Simulations are carried out for a domain extending from 10° S to 30° N and 45° W to 45° E, covering the large West African region, at a resolution of 80 km. Lateral forcings are provided by six hourly ERA-I re-analyses and the integrations were carried out between 1 January 1989 and 31 December 2010 (including one year of spin-up). Only runs from 2003 to 2009 have been retained to be compared with the observed meteorological data and to drive the crop models.

Although our goal is to assess both the influence of the physical parameterizations on the simulated yield bias and the uncertainties linked to the choice of one scheme over another. For computational cost reasons, it was not possible to test all of the combinations. Three sets of experiments were thus designed to address the sensitivity to the model settings and internal variability. As the agriculture of the Sudano–Sahelian zone is highly dependent on rainfall, we focus on parameters that have been previously identified to exert the largest influence on rainfall in Africa (Pohl *et al* 2011): convective and shortwave (SW) radiation schemes (Set #1), the land surface model (LSM) and land use (LU) categories (Set #2), forced versus stochastic components of the regional climate variability (Set #3, through one ensemble simulation). All of the other parameters are fixed: the Yonsei University planetary boundary layer (Hong *et al* 2006), WRF Single-Moment 6-Class cloud microphysics (Hong and Lim 2006), the rapid radiative transfer model longwave radiation scheme (Mlawer *et al* 1997) and the Monin–Obukhov surface layer. More information about the model settings described below is given in table 1 and in the supplementary material.

Set #1. SW radiation and atmospheric convection

SW radiation schemes can be used to estimate the amount of energy available at different altitudes, e.g. the energy of an air parcel at the surface, while convective parameterization schemes (CPSs) are of primary importance for rainfall, especially in regions receiving predominantly convective rainfall, as is the case in West Africa. Set #1 addresses the sensitivity to these two types of settings. Three SW schemes and four CPSs are tested in this paper; their main characteristics are detailed in table 1 (and the supplementary material). For this set of experiments, the LSM is set to the Noah LSM and LU is set to the USGS (United States Geological Survey) LU map.

Set #2. LSM and LU

Atmospheric models are coupled to LSMs to resolve the fluxes at the interface between the continents and the atmosphere. They are forced by atmospheric fields and use global-scale soil and surface LU datasets. LU maps consist of typologies (e.g. 20 or 24 categories such as agriculture, deciduous forests, grasslands, etc.), where each typology is characterized by specific albedo, soil moisture, surface roughness and emissivity values. In this set of simulations, four distinct LSMs and two LUs are tested. Due to the results inherited from Set #1, the SW scheme is set to Dudhia and the CPS is set to Kain–Fritsch with the modified trigger function (KF-t, table 1). This is necessary in order to isolate the specific effects of the LSM and the LU data, when all other settings are constant.

Set #3. Ensemble simulation

In this Set #3, we quantify the amplitude of the uncertainties associated with the chaotic component of the regional atmosphere in our West African domain (hereafter referred to as the 'internal variability' of our model, IV). We then compare it to the changes induced by the settings modified in Sets #1-2. A 10-member ensemble simulation is therefore performed by initializing the integrations on January 1st at 0 h UTC, and then every 6 h, thus providing 10 different initial conditions. This simulation was performed using a unique physical configuration: the Dudhia SW scheme, the KF-t CPS, the Noah LSM and the MODIS LU data.

2.4. Crop model simulations

In order to span some of the uncertainties in crop modeling, which have been shown to be an important contributor to the overall uncertainty in climate impacts (e.g. Asseng *et al* 2013), we use two different crop models, SARRA-H and EPIC, to simulate Benin maize yields and Niger pearl millet yields.

2.4.1. The SARRA-H crop model

The SARRA-H v32 (Système d'Analyse Régionale des Risques Agroclimatiques-Habillée; http://sarra-h.teledetection.fr/SARRAH_Home.html) crop model (Dingkuhn *et al* 2003) was developed by CIRAD (Centre International de Recherche Agronomique). Based on a water balance model, it calculates the attainable yield under water-limited conditions by simulating the soil water balance, potential and actual evapotranspiration, phenology, potential and water-limited assimilation, and biomass partitioning (e.g. Kouressy *et al* 2008, the supplementary material in Sultan *et al* 2013). Soil nitrogen balance processes are not simulated. The SARRA-H model is particularly suited for the analysis of climate impacts on cereal growth and yield in dry tropical environments (e.g. Sultan *et al* 2013, Baron *et al* 2005, Sultan *et al* 2005). Trial and on-farm data were used to calibrate and validate the model for local varieties of Niger millet (Traoré *et al* 2011, Sultan *et al* 2013) and Benin maize (Allé *et al* 2014). Both varieties have a growth-cycle length of approximately 90 days.

Table 1. Parameterization scheme characteristics and references.

Shortwave schemes	Characteristics	Interactions	Reference
Dudhia	Simple downward calculation.	Water vapor absorption. Cloud albedo and absorption. No ozone effect.	Dudhia (1989)
RRTMG (Rapid Radiative Transfer Model)	Spectral method (14 bands).	Cloud fractions. Ozone and CO_2 profile. Trace gases. Aerosols. Top of atmosphere and surface diagnostics for climate.	Iacono *et al* (2008)
Goddard	Spectral method (11 bands).	Clouds. Ozone profile. CO_2 fixed. Aerosols.	Chou and Suarez (1994)

Convective schemes	Characteristics	Reference
Kain–Fritsch	Entraining-detraining mass flux scheme. Triggered by CAPE, Cloud depth, CIN and sub-cloud mass convection. Closure assumption: CAPE.	Kain (2004)
Kain–Fritsch trigger (KF-t)	Kain–Fritsch with a modified trigger function including moisture advection here.	Kain (2004), Ma and Tan (2009)
Betts–Miller–Janjic (BMJ)	Convective adjustment scheme. Triggered by CAPE, cloud depth and cloud-layer moisture. Closure assumptions: CAPE and cloud-layer moisture.	Betts (1986), Betts and Miller (1986), Janjic (1994)
Tiedtke	Entraining-detraining mass flux scheme of a cloud ensemble. Triggered by CAPE, cloud depth and moisture convection. Closure assumption: CAPE.	Tiedtke (1989), Zhang *et al* (2011)

Land surface models	Characteristics	Reference
No LSM	No land surface model, i.e. no temperature or soil moisture prediction.	
Thermal diffusion	5-layer soil temperature model. Soil moisture fixed with a land-use and season-dependent constant value. No explicit vegetation effect.	Dudhia (1996)
Noah	4-layer soil temperature and moisture (and ice) model with canopy moisture prediction.	Chen and Dudhia (2001)
Rapid update cycle (RUC)	>6-layer soil model. Includes temperature, moisture (and ice) and vegetation processes.	Smirnova *et al* (2000), Benjamin *et al* (2004)
Pleim–Xiu	2-layer force-restore soil temperature and moisture model. Includes vegetation.	Xiu and Pleim (2001)

Land use	Characteristics	Reference
US geological survey (USGS)	24 land use categories, derived from NOAA's Advanced Very high resolution radiometer sensors.	Anderson (1976), Hitt (1994)
Moderate resolution imaging spectroradiometer (MODIS)	20 land use categories.	Friedl *et al* (2002)

2.4.2. The EPIC crop model

The EPIC crop model (Williams *et al* 1984, Williams 1990, Williams and Singh 1995) includes a fine description of soil processes and takes carbon–nitrogen dynamics into account. The calibration was performed with a multi-location approach in the subhumid savanna zone of West Africa using data from station and farm fertilizer experiments (Gaiser *et al* 2010, Srivastava and Gaiser 2010). The EPIC model is used to simulate 90-day cultivars of Benin maize (Ramarohetra *et al* 2013) and Niger pearl millet.

Both crop models, forced by *in situ* climate data, were evaluated against Food and Agriculture Organization (FAO) crop yield data for the two sites (figure S1). Correlations between the observed and simulated yields were significant for both models at the two sites (close to 0.6 for millet in Niger and 0.78 for maize in Benin for both models) and the EPIC model accurately reproduces the mean yield of Benin maize and Niger millet. However the SARRA-H model overestimates the mean yield of both Niger millet and Benin maize. This overestimation is a common shortfall in many crop modeling studies (e.g. Challinor *et al* 2004, Bondeau *et al* 2007, Ramarohetra *et al* 2013) and is likely due to a lack of nitrogen stress in the model. More details on this evaluation are provided in the supplementary material.

2.5. Evaluation protocol

In this paper, we adopt the three-tier hierarchical approach described by Morse *et al* (2005; figure 2). A comparison of the ERA-I and WRF simulations with the corresponding observed variables is carried out in a tier-1 evaluation. Since Oettli *et al* (2011) showed that, among the climate variables derived from the RCM, precipitation and radiation are the most likely to induce errors in the simulated crop yields, this paper only concentrates on the effects of these two variables; the other climate variables (temperature, relative

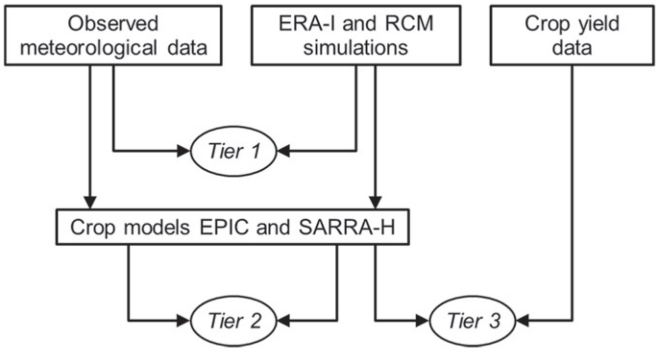

Figure 2. Schematic representation of the three-tier evaluation approach. Rectangular boxes represent sources of data, while oval boxes indicate the different types of evaluation. Adapted from Morse *et al* (2005).

humidity and wind) are taken from *in situ* observations. In a tier-2 evaluation, the essential reference data are precipitation and radiation (as in tier-1), but the data are integrated into the two crop models to produce an estimate of the crop yields. However, the tier-2 evaluation does not validate the crop model *per se* since the objective of the tier-2 evaluation is not to produce an accurate yield prediction, as is the case for the tier-3 evaluation. By using a tier-2 evaluation, we will be validating the ERA-I and WRF output against the observed meteorological *in situ* data, but in a situation where the precipitation and radiation fields have been integrated and synthesized to produce crop yields. For both crop models, *in situ* climate data (our reference climate) are first used to simulate the reference yields for Niger millet and Benin maize over the 2003–2009 period. Then, the crop models are forced using ERA-I and climate variables simulated by the WRF model (three sets of experiments, see paragraph 2.3). The deviation of these alternative simulated yields from the reference yields gives an estimate of the errors that result from forcing the climate variables.

In this paper, we consider the climate inputs from the WRF or ERA-I models as the most suitable for crop yield simulations as they minimize the distance between the simulated yields and the reference yields obtained with *in situ* meteorological data. We were also able to validate the resulting simulated yields against the observed yield data (tier-3 evaluation); however, since the objective of this paper is to assess the sensitivity of the simulated crop yield to the RCMs biases rather than predict accurate yields in the two sites, the results reported in this paper are mainly dedicated to the tier-1 and tier-2 evaluations.

We used the same metric for the tier-1 and tier-2 evaluations to measure the distance to the observed *in situ* data. We calculated the mean bias error (% MBE) of the climate inputs and simulated yields relative to the observed seasonal climate variables (tier-1 evaluation) and simulated yields using the observed *in situ* climate variables (tier-2 evaluation). The % MBE is defined as

$$\%\mathrm{MBE} = \frac{1}{N}{}_{*}100_{*}\sum_{i=1}^{N}\frac{\left(x_i - x_{0i}\right)}{x_{0i}},$$

where x_{0i} is the value of the baseline and x_i, is the value to be tested.

The uncertainties are estimated by calculating the coefficient of variation (CV) of the variables derived from the different runs (climate variables or yields calculated using the different WRF configurations or the different members of the ensemble simulation). The CV is defined as follows:

$$\mathrm{CV} = 100_{*}\frac{\sigma}{\mu},$$

where σ is the standard deviation of the values of the considered variable and μ is the averaged value of the considered variable.

3. Results

3.1. Overview of the simulated yield biases and uncertainties

Simulated yields using ERA-I data directly show biases with an amplitude higher than 20%, reaching up to −77.82% for the SARRA-H Niger millet yields (figure 3: gray dots, and table 2). The use of the WRF model to downscale the ERA-I climate data can reduce the bias in the simulated yields at both sites and for both crop models; for example, the amplitude of the mean bias error (%MBE) for the ensemble mean (in dark green) is lower than 15%. Yet, the use of the WRF model can also introduce large uncertainties due to the choice of parameterization schemes (in red): the % MBE for the simulated yield using different physical configurations ranges from −100% (crop failure) to +84.48% (table 2) and the CV for its %MBE is higher than 39% (table 2). The effect of the choice of each parameterization will be detailed later in this paper. The internal variability of the WRF model, even for a moderately sized domain (see figure 1), notably compared to the much larger CORDEX-Africa domain (Giorgi *et al* 2009), also induces non-negligible uncertainties in the simulated crop yields (green dots).

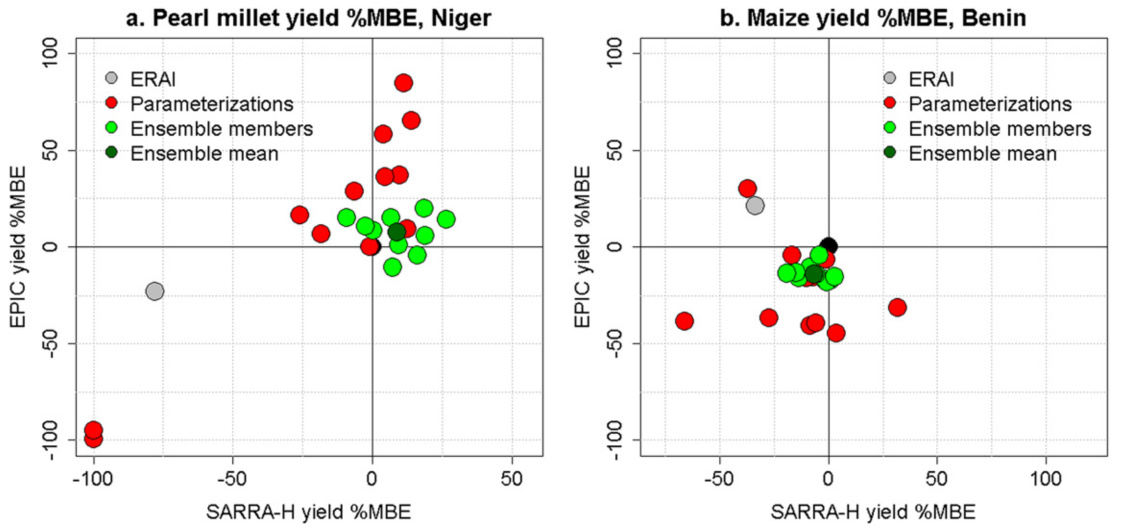

Figure 3. %MBE of the simulated yields. %MBE of the EPIC yields versus %MBE of the SARRA-H yields for (a) Niger millet and (b) Benin maize. Dots represent the mean %MBE for the simulated yields with models forced by raw ERA-I precipitation and SW radiation outputs (gray), by the outputs of the WRF model under different physical parameterizations (red) and by the 10 members of the ensemble simulation (light green). Dark green dots represent the mean of %MBE of the yields simulated using the ensemble simulation.

The largest difference of yield %MBE between two members of the ensemble simulation ranges between roughly 14% (18.08%–4.36%) for the EPIC Benin maize yields and 34% (25.63% + 8.32%) for the SARRA-H Niger millet yields (table 2). However, the uncertainties in the crop yield induced by the internal variability of the WRF model remain lower than those induced by the model parameterizations with an inter-member yield %MBE CV lower than 10% (table 2).

3.2. Influence of climate variables on the simulated crop yields

Depending on the crop model and the considered crop and site, the simulated yields are not sensitive to the same climate variable characteristics and the yield %MBE differs (figure 3). In this section, the main climate characteristics leading the simulated crop yields are identified.

Precipitation and radiation errors result in errors in the simulated yields (figure 4). When considering similar variations of the climate variables, the climate variable with the most marked influence on the %MBE of the simulated crop yields depends on the location and crop model considered.

Water is a limiting factor at the first order, especially for the Niger millet yields which are highly sensitive to a change in the total rainfall (figure 4, top). This is the case even for the Niger millet cultivar simulated with the SARRA-H model, which requires less water to reach its attainable yield. Once the water demand (approximately 600 mm) is met, the simulated SARRA-H Niger millet yields no longer depend on the total water amount. The total rainfall is not a limiting factor for Benin maize growth. When using the EPIC model, high rainfall intensity leads to nitrogen leaching, leading in turn to nitrogen stress which then restricts crop development and grain formation (figure 4(d)). In the SARRA-H crop model, the rainfall intensity has no influence on soil fertility and radiation is the most limiting climate variable for the Benin maize yield (figure 4(c)).

Ranking of the climate variables relative to the explained variance of simulated yield when included in a multiple linear regression. The climate variables taken into account are the annual cumulative rainfall, mean daily rainfall and mean daily radiation. The climate variables on the left explain the largest fraction of the variance whereas the variables on the right explain the lowest fraction for the simulated SARRA-H Niger millet, the EPIC Niger millet, the SARRA-H Benin maize, the EPIC Benin maize and the simulated SARRA-H Niger millet when the annual rainfall amount remains below 600 mm.

Large biases in the simulated Niger millet yields (up to −77% for SARRA-H) using the ERA-I model come from the strong biases in the ERA-I annual rainfall and rainfall intensity (roughly −70% and −74%, respectively; table 2). The underestimation of the rainfall intensity in the ERA-I model results in an overestimation of the EPIC simulated Benin maize yields, while the underestimation of radiation in the ERA-I model results in the underestimation of the yield by roughly −34%.

Using the WRF model to downscale the ERA-I climate data, the model-output climate variables and then the simulated crop yields generally show larger biases than the ERA-I climate variables. These biases are strongly dependent on the chosen physical configuration of the WRF model (CV, table 3). Yet, these

Table 2. Overview of the climate variables and the %MBE of the simulated yields.

		Niger					Benin				
					Millet yields					Maize yields	
		Annual rain	Daily rainfall	Radiation	SARRA-H	EPIC	Annual rain	Daily rainfall	Radiation	SARRA-H	EPIC
Reference		522.35	6.07	5353.99	1202.75	281.71	1289.81	7.3	4708.72	4302.51	1245.74
ERAI %MBE		−70.47	−73.48	11.13	−77.82	−23.11	−5.12	−17.26	−5.95	−33.6	21.21
Parameterization sets											
Median %MBE		106.92	45.63	12.51	7.22	27.54	72.91	65.48	9.6	−13.67	−34.11
Max. %MBE	−	−100	−100	–	−100	−99.28	−100	−100	−4.68	−100	−100
	+	291.06	106.86	29.95	26.5	84.48	182.36	143.18	49.22	31.88	29.93
%MBE CV		72.33	50.51	5.23	47.02	46.78	53.95	37.27	10.96	39.91	42.52
Ensemble simulation											
Mean %MBE		11.64	3.16	13.75	8.99	6.19	5.77	12.08	11.15	−10.18	−14.1
Max. %MBE	−	0.06	−13.34	13.14	−8.32	−13.13	−2.58	3.42	9.57	−22.11	−18.08
	+	36.22	24.71	14.29	25.63	18.87	15	19.86	12.24	−1.33	−4.36
%MBE CV		9.34	11.94	0.33	9.12	9.34	5.92	5.12	0.88	7.22	4.66

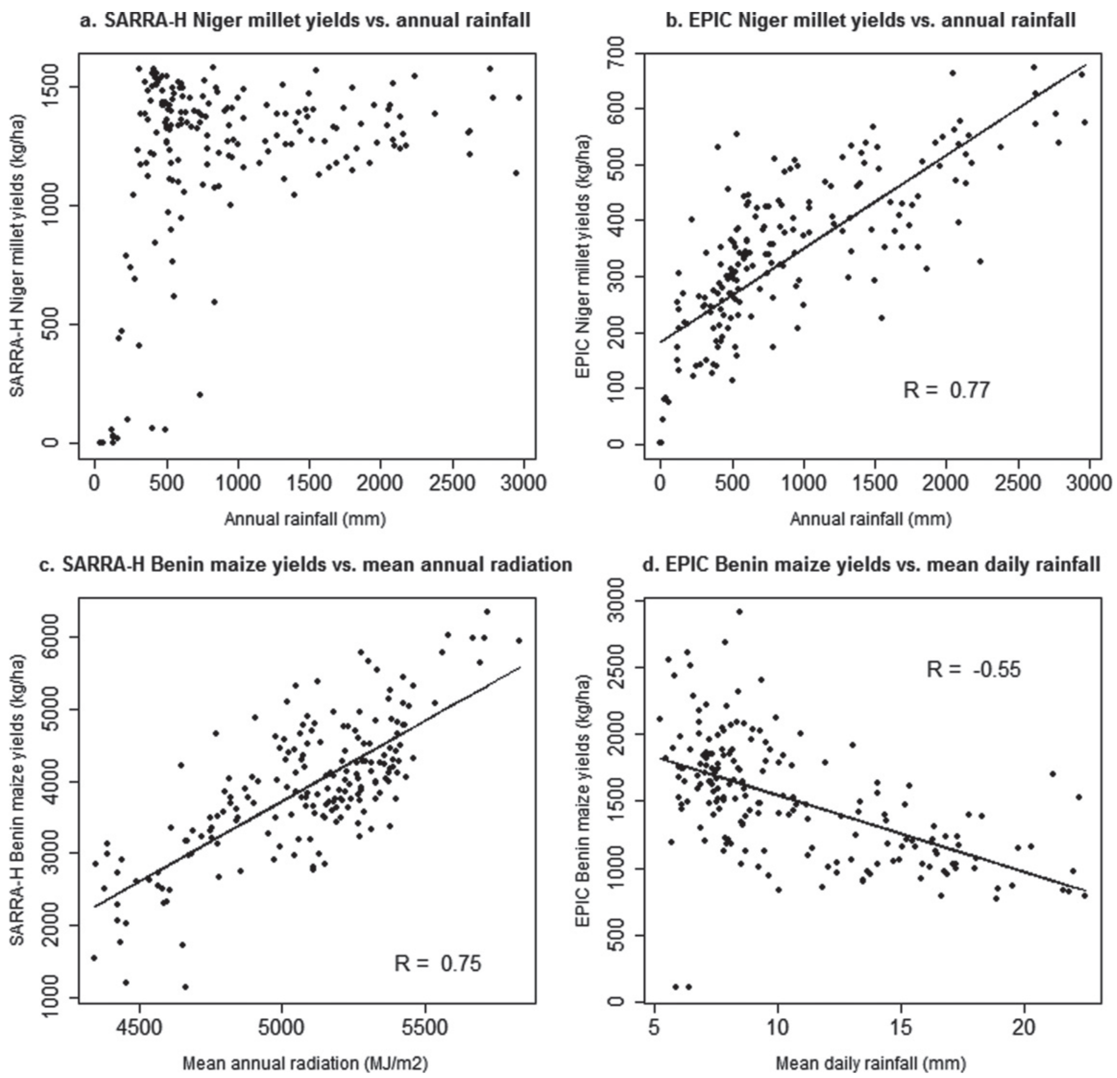

Figure 4. Relationships between the %MBE of the simulated yields and the %MBE of the forcing climate data. The %MBE of the simulated yield versus the %MBE of the dominant climatic variables: (a) the %MBE of the SARRA-H Niger millet yields versus the % MBE of the annual rainfall, (b) the %MBE of the EPIC Niger millet yields versus the %MBE of the annual rainfall, (c) the SARRA-H Benin maize yields versus the radiation %MBE, and (d) the %MBE of the EPIC Benin maize yields versus the %MBE of the mean rainfall intensity. This figure is based on all of the simulated yields (using the reference, ERA-Interim and WRF precipitation and radiation data) used in this study.

biases are strongly reduced for some configurations. The following section investigates the influence of each tested physical parameterization on the simulated climate variables and yields.

3.3. Effect of the different physical parameterizations tested on crop yield

The choice of the WRF physical parameterizations strongly modulates the climate variables relevant to crop yield simulations, thus resulting in high uncertainties in the crop yields (table 2 and figure 3). Among the different parameterizations, the choice of a LSM that takes the moisture dynamics into account is of primary importance for the simulation of realistic rainfall: when there is no soil moisture prediction ('No LSM' or 'Thermal diffusion' scheme), there is no moisture recycling and then rainfall and the simulated crop yields are generally dramatically underestimated, if not null (table 2 and figure 5(a)), especially in Niger where a larger part of the humidity comes from recycling. Climate variables derived using the other LSMs lead to a %MBE amplitude for the Niger millet yields that is lower than 15% (table 3), except for the Pleim–Xiu scheme, for which the overestimation of the precipitation leads to an overestimation of the EPIC Niger millet yields by roughly 29%. The Pleim–Xiu scheme results in simulated Benin maize yields that are significantly lower than in the other schemes; the underestimation of the EPIC Benin maize yields is due to the high daily rainfall overestimation in the Pleim–Xiu scheme while the underestimation of the SARRA-H Benin maize yield is due to an underestimation of the incoming radiation (table 3). The Pleim–Xiu LSM tends to favor larger rainfall amounts than the RUC and Noah LSMs, as already highlighted

Table 3. %MBE of the climate and simulated yields for each of the parameterization schemes. Bold cells indicate the used parameterizations for the ensemble simulation.

		Niger					Benin				
					Millet yields					Maize yields	
		Annual rain	Daily rainfall	Radiation	SARRA-H	EPIC	Annual rain	Daily rainfall	Radiation	SARRA-H	EPIC
SW radiation schemes	**Dudhia**	**8.13**	**−11.45**	**10.58**	**−18.39**	**6.63**	**24.43**	**22.71**	**9.46**	**−1.02**	**−6.79**
	RRTMG	199.95	88.84	8.9	3.83	58.25	127.44	100.07	4.84	−8.71	−40.71
	Goddard	291.06	129.2	14.22	13.83	65.49	182.36	143.18	10.2	3.59	−44.43
CPS	Kain-Fritsch	279.66	106.86	10.78	11.12	84.48	148.05	110.68	16.47	31.88	−31.6
	KF-trigger	**176.9**	**89.02**	**13.87**	**9.64**	**36.9**	**60.85**	**55.75**	**9.28**	**−5.65**	**−39.17**
	BMJ	121.51	12.47	10.99	4.46	36.36	110.95	80.18	6.66	−6.89	−15.32
	Tiedke	87.45	67.11	9.29	−26.19	16.07	125.79	107.99	0.26	−27.52	−36.48
LSM	**Noah**	**24.42**	**7.58**	**13.69**	**12.47**	**9.15**	**−6.59**	**6.3**	**10.61**	**−10.17**	**−15.8**
	No LSM	−100	−100	29.95	−100	−99.28	−100	−100	49.22	−100	−100
	Thermal dif	−97.93	−78.09	18.99	−100	−94.8	−13.69	−2.74	4.21	−37.17	29.93
	RUC	8.52	−10.21	13.84	−1.04	0.14	−11.53	−6.16	**10.66**	−16.94	−4.48
	Pleim–Xiu	94.52	51.73	3.35	−6.46	28.77	19.3	34.93	−4.68	−66.11	−38.23
LU	USGS	24.42	7.58	13.69	12.47	9.15	−6.59	6.3	10.61	−10.17	−15.8
	MODIS	**8.18**	**3.29**	**14.29**	**26.5**	**14.15**	**−2.58**	**4.93**	**12.19**	**−8.54**	**−10.77**

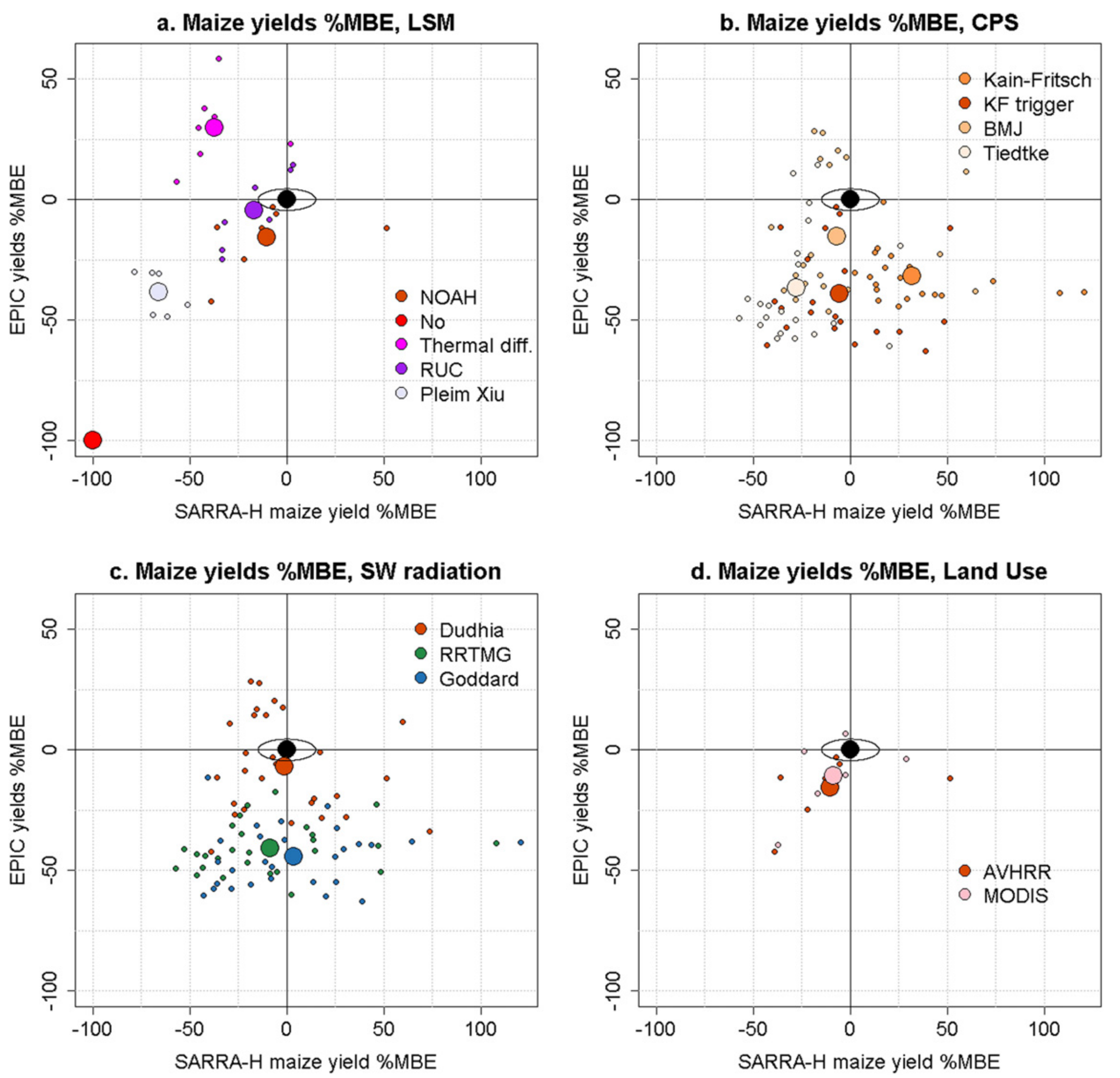

Figure 5. Influence of WRF parameterization on the simulated yield %MBE. %MBE of the EPIC yields versus %MBE of the SARRA-H yields for Benin maize for each tested parameterization: (a) land surface models, (b) convection parameterization schemes, (c) shortwave radiation schemes and (d) land use maps. Each small dot represents one simulation (for each of the seven years for figures (a) and (d), for the 7 × 3 SW schemes for (b) and the 7 × 4 convective schemes for (c)) and the larger dots represent the average of the simulated yields for each configuration.

over East Africa by Pohl *et al* (2011), who linked it to a larger simulated surface evapotranspiration in the Pleim–Xiu model. These authors suggest that the simplified vertical profiles of soil moisture in the Pleim–Xiu LSM (two layers measuring 1 and 100 cm deep) may accelerate evapotranspiration processes. In turn, this might increase soil moisture recycling and cloud cover and decrease incoming radiation.

The second most important parameterization for the crop yield simulation is the CPS. CPSs have a strong influence on both rainfall and radiation characteristics and can result in significant uncertainties in the simulated crop yields (figure 5(b)). The %MBE of the SARRA-H simulated Benin maize yields goes from less than −50% to over +100% and it is driven by radiation. The %MBE of the EPIC simulated Benin maize yields has its smallest value when the BMJ CPS is used. This is explained by the rainfall distribution. In West Africa, the BMJ scheme leads to a more realistic distribution of the precipitation than the Kain–Fritsch and Tiedtke schemes (figure S2 and table 3). The latter two schemes systematically overestimate the rainfall intensities, and the KF-t scheme results in an underestimation of the number of rainfall events of less than 25 mm, compensated by an overestimation of the number of daily rainfall events higher than this threshold. However, this good performance obtained with the BMJ scheme in terms of the daily rainfall simulation cannot be generalized to other tropical regions, as shown for instance by Crétat *et al* (2011b) over Southern Africa. Using the EPIC model, the simulated Niger millet yields are more influenced by the CPS scheme (with the %MBE ranging from 16% to over 84%) than the yields simulated with the SARRA-H model (table 2). When using the SARRA-H crop model, a large overestimation of the rainfall does not result in comparable overestimations of the simulated Niger millet yields (figure 4(a)).

Table 4. Ranking of the climate variables relative to the explained simulated yield variance.

SARRA-H Niger millet	Variable	Mean daily rainfall	Annual radiation	Annual rainfall
	Cumulative explained variance (R^2)	0.12	0.18	0.18
SARRA-H Niger millet (annual rainfall < 600 mm)	Variable	Annual rainfall	Mean daily rainfall	Annual radiation
	Cumulative explained variance (R^2)	0.48	0.52	0.53
EPIC Niger millet	Variable	Annual rainfall	Annual radiation	Mean daily rainfall
	Cumulative explained variance (R^2)	0.59	0.63	0.59
SARRA-H Benin maize	Variable	Annual radiation	Annual rainfall	Mean daily rainfall
	Cumulative explained variance (R^2)	0.56	0.61	0.62
EPIC Benin maize	Variable	Mean daily rainfall	Annual radiation	Annual rainfall
	Cumulative explained variance (R^2)	0.3	0.34	0.34

Among the tested radiation schemes, the Dudhia SW scheme is the one that minimizes the overestimation of both total rainfall and rainy day intensity (table 3); this tendency to favor drier conditions is consistent with the results presented in Pohl *et al* (2011). For the EPIC yields, this leads to lower biases than the other SW schemes. The SARRA-H yields are not very sensitive to overestimations of the rainfall amounts (for Niger millet) or intensity (for Benin maize). The RRTMG and Goddard schemes do not lead to high biases in the SARRA-H yields (figure 5(c)); for both sites, radiation is the main driver of the SARRA-H yields. The simulated radiation shows relatively low uncertainties (the radiation biases are of the same order for all SW schemes), leading to low uncertainties in the SARRA-H yields. Thus the SW schemes, mainly influencing simulated rainfall, induce high uncertainties in the EPIC yields but have a relatively lower influence on the crop yields simulated with the SARRA-H model.

The LU maps tested in this study do not produce large differences in the simulated yields (figure 5(d) and table 3).

Finally, within a crop-modeling framework and over the tested parameterizations, it is very important to choose an appropriate LSM, given the high biases in the rainfall induced by using a LSM that is too simplistic. Then, as the CPS has a significant influence on both rainfall and radiation, this parameterization should be carefully set. The SW radiation scheme mainly drives precipitation and can be important as well. In contrast, the choice of the LU scheme seems to only have a moderate influence on rainfall and radiation and thus on the yields.

3.4. Internal variability

In this section, we run the same experiment 10 times by modifying the initial conditions at the first model time step. The physical package and all other settings are constant in all of the simulations (members) of the ensemble. This allows disentangling the forced (reproducible) and stochastic (internal, or irreproducible) fractions of the simulated climate variability. Our idea here is to compare and rank the magnitude of the uncertainties due to the chaotic component of the regional climate, materialized by the internal variability, and those related to modifications of the physics of the model. At the first order, rainfall is generally the main driver of simulated crop yields; the WRF model was then set to the configuration that minimizes the rainfall biases. This configuration combines the Dudhia SW scheme, the KF-t convective scheme, the NOAH LSM model and MODIS LU data.

We previously showed that when the WRF model is used with an appropriate configuration to downscale the ERA-Interim climate data, the bias in the simulated yields is considerably reduced (figure 3). This can be linked to the dramatic decrease in the simulated rainfall amount and the intensity biases (table 2, ensemble set). However, the internal variability of the WRF model also introduces non-negligible uncertainties in the simulated crop yields. The 10-member simulation leads to uncertainties in rainfall, for which the annual rainfall %MBE ranges from 0% to 36% in Niger and from −2.58% to 15% in Benin (table 2). These uncertainties in the simulated yields can be linked to those in the mean states of the radiation and rainfall characteristics as well as to intraseasonal variations (e.g. Ramarohetra *et al* 2013). Following Crétat *et al* (2011a), the reproducible fraction of day-to-day rainfall and radiation is calculated for

Table 5. Coefficients of variation of the simulated yields, mean radiation and intra-seasonal precipitation descriptors.

	Coefficients of variation	
	NIGER	BENIN
SARRA-H yield	0.53	0.13
EPIC yield	0.32	0.11
Onset	0.22	0.02
End of rainy season	0.04	0.01
Duration	0.47	0.02
Total rainfall	0.37	0.14
Number of rainy days	0.39	0.04
Mean intensity	0.54	0.13
Number of dry spells	0.40	0.23
Mean duration of dry spells	0.14	0.07
Mean radiation	0.01	0.01

the June–July–August–September period of each year as the ratio between $V(X)$, the daily variance of all members (i.e. 122 days duplicated 10 times) and $V(\bar{X})$, the daily variance of the ensemble mean (122 days): $f = \frac{V(\bar{X})}{V(X)}$.

On average, over the seven years, the reproducible fraction of the day-to-day rainfall is approximately 30% for both sites (29% in Niger and 31% in Benin). The inter-annual variability of these scores remains quite low: it ranges from 21% to 35% in Niger and from 25% to 37% in Benin. Therefore, even for a moderate-sized domain (figure 1), the rainfall intra-seasonal variability is mainly driven by the stochastic component of the WRF model rather than by ERA-I forcing. Although the scores are a little higher, the day-to-day radiation variations are also strongly led by the model's internal variability, with averaged reproducibility values of 75% and 58% for the Niger and Benin sites, respectively.

In order to link the intra-seasonal precipitation descriptors to the simulated yield variability in the ensemble experiment, the reproducibility of these descriptors has been investigated for the year 2006 (table 5). In Niger, the least reproducible descriptors are the mean intensity of precipitation, the length of the rainy season and the number of dry spells with coefficients of variation (CV) across the ensemble members of 0.54, 0.47 and 0.40, respectively. In Benin, the least reproducible descriptors are the number of dry spells (CV = 0.23), the mean total rainfall (0.14) and the mean intensity of precipitation (0.13).

CV statistics are preferred to standard deviations to better compare the various descriptors considered here, since they have different units. Large CV values denote strong differences from one ensemble member to another, and are thus indicative of a strong internal variability (i.e. chaotic or local component) and a weak to moderate large-scale forcing prescribed by the reanalyses.

Intra-seasonal precipitation descriptors controlling the simulated yield variability within the ensemble experiment were identified using a multiple regression analysis. For the SARRA-H Niger millet and the EPIC Benin maize, the simulated yield variability is mainly driven by the number of dry spells with coefficients of determination (R^2) of 0.52 and 0.31, respectively (not shown). For the EPIC Niger millet, the total rainfall during the rainy season explains 0.47 of the yield variability while the SARRA-H Benin maize yield variability is mainly explained by the number of rainy days ($R^2 = 0.4$).

The variability of the mean intra-seasonal radiation and precipitation descriptors explains 0.58–0.99 of the yield variability (not shown). However, the timing of events such as dry spells or heavy rainfall explains up to 0.42 of the yield variability.

Therefore, internal variability of the WRF climate model has a non-negligible impact on the simulated rainfall and radiation mean state and intra-seasonal variability, and this translates into uncertainties in the simulated crop yields that should be taken into account.

4. Conclusion and discussion

A sensitivity analysis of the state-of-the-art WRF RCM has been conducted to assess its performance and to quantify uncertainties for the crop yield simulations of Niger millet and Benin maize in two sites in West Africa. It is challenging to account for all of the sources of uncertainties in a RCM and to quantify their respective effects on the simulated climate and subsequently simulated yields since these uncertainties may arise from a wide number of parameters and simulation choices (such as the size, location or resolution of the domain, the model physics, the lateral boundary conditions, etc). Over West Africa, parameterizations of deep atmospheric convection (e.g. Flaounas *et al* 2010, Sylla *et al* 2011, Im *et al* 2014), SW radiation (e.g. Domínguez *et al* 2010), LSMs (e.g. Domínguez *et al* 2010, Im *et al* 2014) and the surface albedo (e.g. Flaounas *et al* 2011) have been shown to have a non-negligible influence on the simulated climate. In this study, we chose to assess the relative influence of these parameterizations (convection, SW radiation, LSM and LU) on simulated crop yields in a combined climate-crop modeling.

We first showed that the choice of the LSM is of primary importance: to simulate realistic rainfalls, the LSM must include a dynamic moisture calculation. This is consistent with previous studies: for example, Koster 2004 showed a strong relationship between soil moisture and precipitation over this region and Im *et al* (2014) showed that LSMs have a significant influence on the calculated rainfall. Among the LSMs that include dynamic moisture calculations, the RUC and Noah models lead to rather similar simulated yields while the Pleim–Xiu LSM, driving heavier rainfall and especially high rainfall intensities, leads to a high underestimation of the Benin maize yields simulated with the EPIC model.

Second, the convective parameterization significantly influences both rainfall and radiation. Among the tested schemes, the BMJ produces daily rainfall intensities that are the closest to the observed intensities, and therefore it is the best scheme for Benin maize simulations with the EPIC model. The KF scheme is the one that overestimates the total rainfall the most (consistent with Crétat *et al* 2011b, Pohl *et al* 2011 and Crétat and Pohl 2012), radiation and then the simulated crop yield for both sites.

Third, the SW radiation scheme, mainly affecting rainfall, has to be chosen carefully. The Dudhia scheme produces significantly less rain than the RRTMG and Goddard schemes, thus minimizing the WRF overcompensation of the ERA-I dry bias and leading to a better crop yield estimation. The RRTMG scheme leads to slightly drier conditions than the Goddard scheme. This is consistent with Pohl *et al* (2011) over East Africa.

Conversely, the tested LU model does not lead to high differences in the crop yields; the uncertainties in the simulated yields are smaller than those induced by the internal variability of the climate model.

In an ensemble experiment, the internal variability of the WRF model has been shown to introduce non-negligible uncertainties in crop yield simulations with differences in the simulated yields reaching up to 30%. Dynamical downscaling can improve the climate forcing upon re-analyses for the simulation of agricultural impacts at the local scale. However, uncertainties arising from both the setting of the parameterizations and the internal variability of the RCM need to be taken into account. Adding a relaxation term in the model's prognostic equation could allow for a more realistic timing of transient perturbations in the regional model, and thus favor lower uncertainties and more realistic variability at fine temporal scales. These relaxation (or nudging) techniques could be advisable for impact studies, although it strongly weakens the coupling between the physics and dynamics of the model (Pohl and Crétat 2013).

Simulated yields have been shown in this study to be strongly sensitive to the RCM physics and the simulation setup. Errors and uncertainties arising from such sensitivity should not be neglected. To minimize these errors, the RCM physics must be carefully set, and to estimate uncertainties coming from the RCM's internal variability, the crop model should be forced by an ensemble simulation of the regional climate. The use of an RCM to downscale climate data for crop yield simulations then implies a cumbersome methodology and high-performance computing facilities, which calls its suitability into question. Moreover, the choice of the best configuration for re-analysis downscaling does not necessarily enable a correction of the GCMs biases (Glotter *et al* 2014).

Although it can probably be considered that the RCM procedure is likely to reveal its added-value in the case of a strong resolution jump with the GCM forcing or re-analyses, allowing for a more realistic resolution of the sub-grid processes, this may not be sufficient since realistic surface boundary conditions (including topography, land-use and sub-surface properties) are also needed. In this regard, due to the scarcity of high-resolution, reliable datasets documenting surface and soil dynamics, climate downscaling over Africa remains a challenging issue.

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