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Evaluation of rainfall simulations over Uganda in CORDEX regional climate models

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Abstract

The study evaluates the ability of ten regional climate models (RCMs) to simulate the present-day rainfall over Uganda within the Coordinated Regional Downscaling Experiment (CORDEX) for the period 1990–2008. The models' ability to reproduce the space-time variability of annual, seasonal, and interannual rainfall has been diagnosed. A series of metrics have been employed to quantify the RCM-simulated rainfall pattern discrepancies and biases compared to three gridded observational datasets. It is found that most models underestimate the annual rainfall over the country; however, the seasonality of rainfall is properly reproduced by the RCMs with a bimodal component over the major part of the country and a unimodal component over the north. Models reproduce the interannual variability of the dry season (December–February) but fail with the long and short rains seasons even if the ENSO and IOD signal is correctly simulated by most models. In many aspects, the UQAM-CRCM5 RCM is found to perform best over the region. Overall, the ensemble mean of the ten RCMs reproduces the rainfall climatology over Uganda with reasonable skill.

1 Introduction

The rainfall pattern over Uganda shows a high degree of spatial and temporal variability compared to other meteorological parameters such as temperature, pressure, and wind. The spatial variation has been attributed to the complex topography (Oettli and Camberlin 2005; Yang et al. 2015), varied vegetation, and existence of large inland water bodies, which modulate the local climate (Thiery et al. 2015). The larger space-

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time characteristics of rainfall over Uganda are mainly controlled by the Intertropical Convergence Zone (ITCZ) and its latitudinal movement, monsoonal winds, and moist westerlies from Congo (Basalirwa 1995), but also, on interannual time scale, by sea surface temperature (SST) gradient fluctuations, particularly the El Niño Southern Oscillation (ENSO) (e.g., Indeje et al. 2000; Mutai and Ward 2000; Mutai et al. 1998; Nicholson and Kim 1997; Ntale and Gan 2004) and Indian Ocean Dipole (IOD) (e.g., Saji et al. 1999). ENSO teleconnections affect the northern and southern regions of Uganda differently. In the south, El Niño leads to higher rainfall amounts and emphasizes the bimodal pattern, while La Niña leads to lower rainfall (Phillips and McIntyre 2000).

In addition, local features such as large inland water bodies and topography introduce a significant modification in the general wind and moisture fluxes over the region, coupled with convective processes that generate a complex pattern with sharp changes of rainfall amounts over short distances (Nicholson 1996). These multiple-scale climatic processes result in varied rainfall regimes throughout the country as presented by Basalirwa (1995). Shortly, a unimodal rainfall regime is experienced in the northern parts of the country, further away from the equator from June to August, whereas a bimodal regime is experienced nearer to the equator, with the major season in March–May and a shorter rainfall season in September–November. Eastern Uganda and some regions close to the equator receive three rainfall seasons exhibiting a trimodal regime, with the third peak centered around July/ August due to the moisture influx from Atlantic Ocean and the moist Congo basins by the westerly winds (Mutai et al. 1998; Ogallo et al. 1988), and a low pressure anomaly related to a secondary convergence zone (Camberlin 2018).

As with many countries of East Africa, Uganda is already experiencing dire consequences of erratic climatic conditions that are associated with regional climatic changes (Anyah and Qiu 2012; Shongwe et al. 2011). Uganda also experiences frequent severe droughts (e.g., Nicholson 2017) with dramatic consequences on the local population, with the most affected region being the "cattle corridor"¹ and, more specifically, the Karamoja region (Nimusiima et al. 2013). The frequency of such episodes coincides with the current reduction in March-May seasonal rainfall (Maidment et al. 2015; Yang et al. 2014). Furthermore, a study by Nsubuga et al. (2014) observed mixed seasonal rainfall trends in southwestern Uganda. This variability is expected to undermine regional sustainable development (Sabiiti et al. 2018) as a result of the region's overreliance on agriculture and other rainfed sectors (e.g., health, energy, and water management) to sustain its economy as well as its relatively low adaptive capacity (IPCC 2013). Within this context, a better understanding of how skillful climate models are in reproducing the observed regional climate patterns is increasingly important, in order to deliver reliable projections of seasonal to interannual rainfall amounts for disaster prevention and, more generally, resource planning.

Climate models have been developed to simulate the climate on a mesoscale, regional, or global scale. The primary tools for understanding the large-scale climate and its projected change under different forcing scenarios are global climate models (GCMs). However, their coarse resolution precludes them from capturing the detailed processes associated with regional climate variability and changes that are required for national climate change assessments (Giorgi et al. 2009; Rummukainen 2010; Wang et al. 2004), especially over regions like Uganda with heterogeneous land surface cover such as lakes, forests, and mountains that modulate the climate signals at fine scales (Giorgi et al. 2009).

When regional climate models (RCMs) are driven by GCMs, biases inherited through the lateral boundary conditions are added to those of the RCM; as a result, downscaling is not always able to improve the simulation skills of large-scale forcing (e.g., Panitz et al. 2014), with cases where the RCM climate change signal can substantially differ from that of the driving GCM (e.g., Dosio and Panitz 2016). However, added value of RCMs in downscaling GCMs is found

especially in the fine scales and in the ability of RCM to simulate extreme events (e.g., Dosio et al. 2015).

Consequently, the use of outputs from RCMs has become a vital and effective tool for studying regional climate change and variability due to their capability of capturing finer spatial and temporal scales that are required for climate change impacts and adaptation studies (Jones et al. 2004; Pal et al. 2007; Wang et al. 2004). Previous studies have focused on assessing the performance of RCMs over the East African region (e.g., Sun et al. 1999a, b; Anyah and Semazzi 2006, 2007; Diro et al. 2012; Endris et al. 2016, 2013; Kipkogei et al. 2016; Ogwang et al. 2014, 2015, 2016; Opijah et al. 2014; Segele et al. 2009) as well as over the Lake Victoria basin (e.g., Anyah 2005; Anyah et al. 2006; Sabiiti 2008; Thiery et al. 2015; Williams et al. 2015), but very few studies have been focused on national scale especially over Uganda (e.g., Mugume et al. 2017a, b; Nandozi et al. 2012; Nimusiima et al. 2014), and in addition, these studies are largely based on the outputs from a single RCM and one observational dataset.

In order to properly understand the biases in RCM simulations, a study needs to make use of an ensemble of RCMs and needs to focus on specific regions, as RCMs can often do well over some areas and worse over the others (Kalognomou et al. 2013). The multi-RCM experiment Coordinated Regional Downscaling Experiment (CORDEX, Giorgi et al. 2009), initiated by the World Climate Research Program of the World Meteorological Organization, aims to provide an opportunity for generating high-resolution regional climate projections which can be used for assessment of future impacts of climate change at regional scales. However, the skills of the RCMs have to be assessed, and their performances evaluated to establish their strengths and weaknesses, before they can be used for generating downscaled projections of the future climate: this evaluation is performed by using appropriate metrics to compare models' outputs against reference data from observations or reanalyses (Islam et al. 2008; Kim and Lee 2003; Lenderink 2010).

In the framework of the CORDEX-Africa project (Hewitson et al. 2012), the ability of RCMs in simulating the East African rainfall is presented in Endris et al. (2013) and Endris et al. (2016), who demonstrate that the models simulate the main features of rainfall climatology adequately, although there are significant biases among individual models. The analysis shows that the multimodel ensemble generally outperforms any individual model, as previously found by Nikulin et al. (2012), Kalognomou et al. (2013), and Kim et al. (2014). Nevertheless, as shown by Nikulin et al. (2012) and Kim et al. (2014), RCMs produce a quasi-systematic dry bias over Uganda, and consequently, more investigations are needed in order to assess during which season the biases are strongest. In addition, Uganda does not lie in any of the targeted homogenous subregions of the East

¹ Area stretching from Karamoja region in the northeast, through central to the southwest of the country.

African domain considered in Endris et al. (2013). Therefore, a national scale-based model skill assessment is necessary.

The aim of this study is to assess the ability of CORDEX RCMs in simulating the rainfall characteristics over Uganda. We also investigate the ability of the models to capture the influence of large-scale features such as ENSO and IOD on Ugandan rainfall. The study is guided by two main questions: (1) How well do CORDEX RCMs reproduce the observed annual and seasonal rainfall patterns over Uganda? (2) How well do CORDEX RCMs replicate the present-day interannual variability of rainfall and the teleconnection with ENSO and IOD?

The study is organized as follows: in Section 2, a brief description of the study area and next the observed and modeled datasets and methods used are presented. In Section 3, the results and discussion begin with the annual rainfall, seasonal rainfall, interannual variability, and the response of regional rainfall to ENSO and IOD. Finally, Section 4 synthetizes the results and concludes the study.

2 Data and methods

2.1 Study area

This study focuses on Uganda, which lies in the East African region, astride the equator between latitudes 4° 12' N and 1° 29' S and longitudes 29° 34' E and 35° 29' E. The central part of the country consists of a relatively flat plateau at an elevation of 1000 to 1300 m asl, with higher ground areas both to the east (e.g., Elgon mountains and Karamoja) and the west (e.g., Rwenzori and Mufumbira mountains). The western part of the country is also dissected by the Western Rift Valley running from north to south at an elevation of 600–900 m asl. Africa's largest lake, Lake Victoria, occupies the southeastern corner of the country. Other significant water bodies include Lake Albert in the west and Lake Kyoga in the center (see Fig. 1).

2.2 Observed and modeled rainfall data

High-quality observational datasets for Africa are scarce, and significant discrepancies exist among different datasets mainly due to first the limited number of gauge stations and second to retrieval, merging, and interpolation techniques (Dosio et al. 2015; Nikulin et al. 2012; Panitz et al. 2014; Sylla et al. 2012). Therefore, in this study, three observed rainfall datasets are utilized. Two gauge-based gridded datasets available at 0.5° spatial and monthly temporal resolution provided by the Global Precipitation Climatology Centre (GPCC; version 7, 1901–2013, Schneider et al. 2015) and the Climate Research Unit (CRU TS3.10, 1901–2012, Harris et al. 2014) are used. In addition, a satellite-gauge combined dataset from the Climate Hazards Group InfraRed Rainfall (CHIRPS, Funk et al. 2015) available at a 0.05° (5 km) spatial resolution from 1981 to

present is used. It should be noted that GPCC was chosen as the reference observational dataset for this study (similar to the previous studies on Africa: Endris et al. 2016, 2013; Favre et al. 2016; Kalognomou et al. 2013 among others). Rainfall from ERA-Interim, with a spatial resolution of 0.75°, has also been used in order to assess the added value of RCMs in comparison to the forcing data over the studied region.

Monthly rainfall (unit: mm/day) output from ten RCMs (Table 1) forced by ERA-Interim reanalysis data (Dee et al. 2011), over the period 1989–2008, has been used. The spatial resolution of the data is 0.44°, corresponding to a horizontal distance of roughly 50 km.

2.3 Methods

In order to compare the RCM outputs to the observations, the modeled data have been adjusted to the reference data grid (i.e., from 0.44° to 0.5°) by applying a bilinear interpolation as in Nikulin et al. (2012), Kalognomou et al. (2013), Favre et al. (2016), and Akinsanola et al. (2017). The same procedure has been applied to ERA-Interim reanalysis data (from 0.75° to 0.5°) and CHIRPS (from 0.05° to 0.5°). Lastly, considering 1989 as a spin-up year for the RCMs' simulations, the study covers the period 1990–2008 (19 years). While the reference dataset GPCC does not provide values for precipitation over Lake Victoria, a mask has been created over the lake for the models and other observational datasets (CHIRPS and CRU) to facilitate consistent comparison.

An initial assessment is made of annual mean rainfall spatial pattern over Uganda (Section 3.1). Each model output and the ensemble mean of the ten RCMs have been compared to observations over the area $(28.75^{\circ} \text{ E}-35.75^{\circ} \text{ E}, 1.75^{\circ} \text{ S}-4.25^{\circ} \text{ N})$, see Supplementary material, Fig. S1). The annual mean rainfall biases of the models, ensemble mean, ERA-Interim reanalysis, and other observations (CHIRPS and CRU) with respect to GPCC have been quantified and mapped (Fig. 2). Complementary metrics, such as the root mean square error (RMSE), have been computed to evaluate the difference between predicted and observed values (Table 2).

Secondly, the rainfall seasonality over the studied region has been assessed by means of Hovm ller diagrams (Section 3.2, similar to previous studies over Africa such as Nikulin et al. 2012; Otieno and Anyah 2012; Akinsanola et al. 2015, 2017). A Hovm ller diagram is a time-longitude or time-latitude depiction of a parameter (e.g., rainfall, temperature), used to assess or diagnose the behavior of a parameter over a span of latitudes or longitudes through time. In our case, we assess the timing and the latitudinal band location of seasonal rainfall over the region (i.e., the seasonal path of the ITCZ). To visualize the observed rainfall seasonality over the region of study, a Hovm ller diagram for GPCC has first been plotted. Next, the disagreement in the rainfall seasonality between the RCMs (including the ensemble mean), ERA-Interim, the other observational datasets



Fig. 1 Topography of the studied region (GTOPO30 USGS, approximately 1 km resolution, unit: m)

(CHIRPS and CRU), and GPCC has been diagnosed and specifically analyzed (Fig. 3) to determine the season when the biases in the models are strongest. In order to synthetically quantify and visualize the individual capacity of the models in simulating the seasonal rainfall pattern, a Taylor diagram (Taylor 2001) has been constructed from the Hovm ller diagrams. The standard deviation (SD), the RMSE, and the correlation between model output and observations quantify thus the model performance (Fig. 4).

Next, we have evaluated the ability of RCMs to reproduce the interannual rainfall variability over the region (Section 3.3). First, we computed the averaged temporal standard deviation for each month in order to distinguish if the RCMs are able, for instance, to simulate the higher interannual variability of the short rains season than the long rains season (section 3.3.1, Fig. 5). This metric allows to verify which month of the year shows realistic interannual variance in the models, compared to the observations. Second, to investigate more deeply the capacity of the RCMs in simulating interannual variability of rainfall, the seasonal standardized rainfall indices (SRIs) derived from the RCMs (including the ensemble mean), ERA-Interim, and the observational datasets have been computed (Section 3.3.2, Fig. 6 and Supplementary material, Fig. S4). SRIs allow to compare more easily the

Acronym	Center of research	RCM	References
BCCR-WRF331	Uni Research and the Bjerknes Centre for Climate Research	WRF331	Skamarock et al. (2008)
CCCma-CanRCM4	Canadian Centre for Climate Modelling and Analysis (Canada)	CanRCM4	Scinocca et al. (2016)
CLMcom-CCLM4-8-17	CLM community	CCLM4-8-17	Rockel et al. (2008)
CNRM-ALADIN52	Centre National de Recherches Météorologiques (France)	ALADIN52	Déqué (2010)
DMI-HIRHAM5	Danmarks Meteorologiske Institut (Denmark)	HIRHAM5	Christensen et al. (2007)
KNMI-RACMO22T	Koninklijk Nederlands Meteorologisch Instituut (Netherlands)	RACMO22T	van Meijgaard et al. (2008)
MOHC-HadRM3P	Met Office Hadley Centre (UK)	HadRM3P	Jones et al. (2004)
MPI-CSC-REMO2009	Max Planck Institute (Germany)	REMO2009	Jacob et al. (2007)
SMHI-RCA4	Sveriges Meteorologiska och Hydrologiska Institut (Sweden)	RCA4	Samuelsson et al. (2011)
UQAM-CRCM5	Université du Québec à Montréal (Canada)	CRCM5	Zadra et al. (2008), Hernandez-Diaz et al. (2013)

 Table 1
 The list of RCMs used in this study

models and observations independently of biases in means and in standard deviations. Indeed, all values of indices are thus expressed in *z*-scores, i.e., the mean is equal to 0 and the standard deviation is equal to 1. In addition, to evaluate the performance of the models, seasonal correlation coefficients with the reference GPCC are calculated over the period 1990– 2008 and are shown in Table 3.

Finally, complementary analysis of the relationship between large-scale oscillations such as ENSO and IOD and rainfall over Uganda has been performed (Section 3.4, Fig. 7). In this study, ENSO has been monitored using two SST indices over the Pacific Ocean: NINO1.2 (an average of SST over 0-10° S and 90-80° W; Trenberth and Stepaniak 2001) and NINO3.4 (an average of SST over 5° S-5° N and 170-120° W; Trenberth 1997). Both SST indices are calculated from the Extended Reconstructed Sea Surface Temperature (ERSST) v5 dataset (Huang et al. 2017) and are provided by the Earth System Research Laboratory.² Note that, to quantify El Niño and La Niña phases (warm and cold episodes, respectively), we used Oceanic Niño Index (ONI) derived from ERSSTv5 dataset and published online³ by the Climate Prediction Centre (CPC) of the National Oceanic and Atmospheric Administration (NOAA).

For IOD, the Dipole Mode Index (DMI, Saji et al. 1999), which quantifies the difference between the area average SST in the western equatorial Indian Ocean ($50-70^{\circ}$ E and 10° S– 10° N) and southeastern equatorial Indian Ocean ($90-110^{\circ}$ E and $10-0^{\circ}$ S), has been used. This index is provided by the Japan Agency for Marine-Earth Science and Technology (JAMSTEC) found on their Application Laboratory website.⁴ A 3-month sliding window correlation analysis between Ugandan rainfall and the SST indices has been performed to evaluate if the models are able to reproduce the ENSO/IOD signature. We have thus verified if the modeled relationship with ENSO/IOD is stronger during the short than the long rains season, as it happens in observations.

3 Results and discussions

3.1 Spatial distribution of annual rainfall over Uganda

The spatial distribution of annual rainfall, as shown by GPCC (Fig. 2a), is relatively uniform over most of the country, with amounts between 3 and 4 mm/day, on average. Nevertheless, along the shores of Lake Victoria, annual rainfall is more abundant and exceeds 4 mm/day. This is associated with land and lake breezes which reinforce convective processes. Moving toward the north east, rainfall decreases toward the semiarid area of Karamoja. Rainfall is relatively rare there, with an annual mean below 2 mm/day.

Looking at the other observational datasets (CHIRPS and CRU, Table 2 and Fig. 2n–o), their root mean square errors, with respect to GPCC, show rather small values (about 0.4), meaning that there is no large bias in the spatial distribution of GPCC mean annual rainfall. It might be noted, however, that both CHIRPS and CRU show a systematic dry bias along the west shore of the lake, signifying that GPCC may overestimate rainfall, of few tenths of millimeters per day, over this peculiar area. These drier conditions over the western shores of Lake Victoria have also been shown by Jury (2017). Also, it can be noted that CRU (CHIRPS) is on average slightly drier (wetter) than GPCC. On the other hand, the ERA-Interim reanalysis tends to show wetter conditions over most parts of the region with larger wet biases along the east shores of Lake Victoria. Inversely, the west shores are drier in the

² https://www.esrl.noaa.gov/psd/data/climateindices/list/

³ http://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ ONI_v5.php

⁴ http://www.jamstec.go.jp/frcgc/research/d1/iod/iod/dipole_mode_index. html



Fig. 2 a Annual mean rainfall (1990–2008) according to GPCC and mean biases over the period quantified as the difference between the models (b-k), ensemble (I), ERA-Interim (m), CHIRPS (n), CRU (o), and GPCC (unit: mm/day)

reanalysis than in observations and also the area just northward of Lake Kyoga.

Contrary to ERA-Interim reanalysis, most of the models (seven out of ten) underestimate the annual

mean rainfall over Uganda. More specifically, the CLMcom-CCLM4-8-17 and MPI-CSC-REMO2009 simulations show a general dry bias (\sim 50% compared to GPCC) over the entire region (Fig. 2d, i; see also in

Table 2Mean annual rainfall (left column) and the spatial root meansquare error (right column) in the annual mean rainfall with respect toGPCC for the models, ensemble, ERA-Interim, CHIRPS, and CRU overUganda. Units: millimeters per day

	Mean	RMSE
BCCR-WRF331	2.92	1.84
CCCma-CanRCM4	4.85	1.71
CLMcom-CCLM4-8-17	1.75	1.85
CNRM-ALADIN52	2.90	1.21
DMI-HIRHAM5	3.06	2.31
KNMI-RACMO22T	2.94	1.23
MOHC-HadRM3P	3.74	1.58
MPI-CSC-REMO2009	1.61	2.02
SMHI-RCA4	2.40	1.77
UQAM-CRCM5	3.95	1.20
ENSEMBLE	3.02	0.94
ERA-Interim	4.22	1.39
CHIRPS	3.42	0.46
CRU	3.21	0.43

The reference is GPCC (mean = 3.35 mm/day). Number of documented grid points is 188

Supplementary material Fig. S1) and exhibit a relative large RMSE (Table 2, see also Dosio et al. 2015; Panitz et al. 2014). On the contrary, two simulations present wetter conditions: CCCmaCanRCM4 and, to a lesser extent, UQAM-CRCM5, with a mean of 4.85 (+45%) and 3.95 (+20%) mm/day, respectively, and a RMSE of 1.71 and 1.21 mm/day, respectively.

Moreover, a quasi-systematic wet bias can be noted over the highest areas of the region, such as over the Elgon Mountain (in the east), the Rwenzori Mountains, and the Lendu Plateau (in the west, along the Albertine Rift, see Fig. 1). These biases, linked to the orography, are particularly marked in the SMHI-RCA4, DMI-HIRHAM5, BCCR-WRF331, and CNRM-ALADIN52 simulations and are also notable in the ensemble mean. The statistical relationship between orography and spatial distribution of biases in mean rainfall of CORDEX simulations has also been shown by Favre et al. (2016) for the South African region.

The ensemble mean of the ten models is generally drier than observation, specifically along the west shores. On the other hand, it has to be noted that the ensemble mean outperforms all individual models and, at the same time, presents a lower RMSE than ERA-Interim (0.94 mm/day against 1.39). A better performance than ERA-Interim is also shown by UQAM-CRCM5, CNRM-ALADIN52, and KNMI-RACMO22T.

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3.2 Seasonal rainfall

The seasonal variation of rainfall over Uganda as displayed by GPCC (Fig. 3a, see also Supplementary material, Fig. S3; (6)) shows that the annual cycle is mainly bimodal with two main rainfall peaks. The first one occurring in March–May is named the "long rains" season and the second one in September–November is named the "short rains" season (Basalirwa 1995). This periodicity in rainfall is principally linked to the latitudinal displacement of the Intertropical Convergence Zone, which crosses the studied region twice a year.

More in details, on the Hovm ller diagram for GPCC, it is shown that the onset of the long rains season, between February and March, tends to synchronically occur over the whole country. Nevertheless, concerning the short rains season, the pattern is less marked and the onset tends to be earlier (August–September) over the center of the country and later (September–October) over the south.

The general pattern shows that the bimodal component is much more pronounced around the equatorial belt, between latitude 1.5° S and 1.5° N (see also the Supplementary material Fig. S_3 ; (3-5)), with the months (July-September) being relatively dry. Inversely, to the north of 1.5° N, the July-September season becomes less dry and shows, to the north of 3° N, wet conditions, with a peak in August. This rainfall peak is associated with the moisture influx from the Congo basin (Mutai et al. 1998; Phillips and McIntyre 2000) that is controlled by the St Helena high centered off south-west Africa. By consequence, over the north of the country, the rainfall annual cycle tends to be unimodal with wet conditions from March to October and drier conditions from November to February (see Supplementary material Fig. **S3**; (1–2)).

Both CHIRPS and CRU, as well as ERA-Interim (Fig. 3n, o, and m, respectively), clearly reproduce the GPCC seasonal pattern, although ERA-Interim tends to show wetter conditions all throughout the year, with larger wet biases during the drier months (January, February) and the beginning of the long rains season (March, April). Maidment et al. (2013) also showed that ERA-Interim overestimates rainfall over Uganda. In their study, the reanalysis (among other gridded datasets such as the ones derived from satellites) is compared to rain gauge records throughout the country for the year period from February to June. They also found that the wet biases in ERA-Interim are particularly marked in February, March, and April. However, in Fig. 3m, we note an exception over the southern part of the region where ERA-Interim presents a slight dry bias from May to September.

Fig. 3 Hovm ller diagrams. a Averaged time-latitude cross section of monthly mean rainfall (color scale bounded at 8 mm/day, interval contour 0.5 mm/day) according to GPCC and the monthly mean rainfall (colors)

and mean biases with respect to GPCC (contour interval 0.5 mm/day and dashed lines are for negative values) for the models (b-k), ensemble (l), ERA-Interim (m), CHIRPS (n), and CRU (o) over Uganda

When analyzing the RCM results, it is evident that almost all the models are able to reproduce the observed bimodal annual cycle. However, most of them (seven out of ten) underestimate the rainfall intensity for the season stretching from March to May, in particular CLMcom-CCLM4-8-17 and MPI-CSC-REMO2009 (which were already identified as the driest simulations). Also, it can be noted that, in addition to the general dry bias, CLMcom-CCLM4-8-17 tends to simulate relatively more rainfall during the short rains season than during the long rains season. This last feature is also noted for BCCR-WRF331, which overestimates the magnitude of the short rains season (which also appears too early) in comparison with the long rains season. Concerning the wetter simulations, CCCma-CanRCM4, UQAM-CRCM5, and to a lesser extent MOHC-HadRM3P tend to produce rainfall all through the year and at all latitudes. It is worth noting that those models also exhibit a more pronounced wet bias in October–November (i.e., the short rains season). Also, a strong overestimation of rainfall in April–May is particularly shown by UQAM-CRCM5 (i.e., the long rains season). By consequence, in the UQAM-CRCM5 simulation, the bimodal component of seasonal rainfall is strongly marked and at all

latitudes including the northern region of the country where the cycle should be more unimodal.

The ensemble mean of the ten models underestimates the rainfall, specifically during the long rains season and, on the contrary, tends to slightly overestimate the rainfall during the short rains season. Nevertheless, it is found that the ensemble mean outperforms all individual models.

The Taylor diagram (Fig. 4) presents a synthetic visualization of the skill of the ten RCMs in reproducing the annual cycle of rainfall over the studied domain as presented by Fig. 3, i.e., the Hovmöller diagrams. The deviation from observations (GPCC, reference data) of each model is quantified by the standard deviation, the correlation coefficient, and the centered root mean square error between the model and observation as shown in Fig. 4 by the light gray curves. It is worth noting that the values are not standardized, and the unit of SD and RMSE is millimeters per day. The SDs show that, with the exception of CLMCom-CCLM4-8-17, CNRM-ALADIN52, KNMI-RACMO22T, and MPI-CSC-REMO2009, all RCMs and the ensemble mean overestimate the seasonal rainfall variance over the country, i.e., the contrast between wet and dry months. CCCma-CanRCM4 and UQAM-CRCM5 (already found to overestimate seasonal mean rainfall) show large values of both SD and RMSE and high correlation coefficients.

Fig. 5 Standard deviation computed over the period 1990– 2008 (unit: mm/day) for Uganda

Fig. 6 Standardized rainfall indices for the annual and December–February (DJF), March–May (MAM), June– August (JJA), and September– November (SON) seasons over Uganda for the 1990–2008 period. Gray shading is the full range of the RCM outputs, and the yellow shading is the 25th– 75th percentile range (i.e., interquartile range)

Finally, the seasonality of rainfall derived from the ensemble mean outperforms all individual models and the ERA-Interim (whose performance remains modest) and is the closest to observations. A better performance than ERA-Interim is shown by MOHC-HadRM3P and UQAM-CRCM5 in terms of correlation coefficient (correlation equal to 0.9). As expected, both observational datasets (CHIRPS and CRU) are very close to GPCC.

3.3 Interannual variability of rainfall

3.3.1 Interannual variability of monthly rainfall

Several studies (e.g., Diro et al. 2011; Endris et al. 2013; Indeje et al. 2000; Mutai and Ward 2000; Philippon et al. 2002) have shown that the short rains season experiences a larger degree of interannual variability than the long rains season. This stronger interannual variability is linked to tropical SST anomalies (i.e., to the phases of ENSO and IOD).

Here, we assess the ability of the RCMs to reproduce these features by computing, for each month, the standard deviation

over the 19 years for the ten RCMs, ensemble mean, ERA-Interim, and the observational datasets (GPCC, CHIRPS, and CRU); results are shown in Fig. 5. With reference to GPCC, it can be shown that the mean standard deviation is strongest in November (SD = 1.73 mm/day) and weakest in January (SD = 0.96 mm/day). Generally, it can also be observed that the short rains season presents an interannual variability slightly stronger than that of the long rains season. CHIRPS and ERA-Interim identify this pattern; nevertheless, ERA-Interim tends to overestimate the standard deviation for all months of the year, while the inverse is observed for CHIRPS for which the standard deviation tends to be generally underestimated. CRU is relatively close to GPCC; nevertheless, the maximum of variance is centered in September instead of November. By consequence, it can be noted that the observational datasets are not in good accordance concerning the interannual variability of monthly rainfall over Uganda. The spread between the three datasets is relatively large concerning this metric.

Compared to GPCC, the interannual variability over Uganda is underestimated by most models (eight out of ten),

Table 3 Pearson correlation coefficients (r) between standardizedrainfall indices (shown in Fig. S4) derived from GPCC and the RCMs,ensemble mean, ERA-Interim, and other observational datasets (CHIRPSand CRU) for the December–February (1st column), March–May (2ndcolumn), June–August (3rd column), and September–November (4th column)umn) seasons and the annual (5th column), over the period 1990–2008

	DJF	MAM	JJA	SON	Annual
BCCR-WRF331	0.83	0.11	0.56	-0.07	-0.13
CCCma-CanRCM4	0.72	0.49	0.69	0.31	0.44
CLMcom-CCLM4-8-17	0.90	0.37	0.57	0.53	0.22
CNRM-ALADIN52	0.85	0.41	0.48	0.60	0.22
DMI-HIRHAM5	0.79	0.30	0.53	0.62	0.15
KNMI-RACMO22T	0.82	0.37	0.57	0.54	0.49
MOHC-HadRM3P	0.81	0.38	0.68	0.68	0.32
MPI-CSC-REMO2009	0.72	0.19	0.34	0.40	-0.38
SMHI-RCA4	0.75	0.09	0.20	0.50	0.10
UQAM-CRCM5	0.85	0.57	0.59	0.80	0.79
ENSEMBLE	0.89	0.51	0.70	0.69	0.45
ERA-Interim	0.75	0.21	0.49	0.63	0.30
CHIRPS	0.98	0.85	0.91	0.83	0.78
CRU	0.94	0.71	0.76	0.77	0.74

Values in bold are significant at the 99% confidence level (t test)

particularly by CNRM-ALADIN52, MPI-CSC-REMO2009, and KNMI-RACMO22T. These three simulations lie outside the observations envelop. On the other hand, BCCR-WRF311 and CLMCom-CCLM4-8-17 overestimate the mean standard deviation particularly for the short rains season. Furthermore, it should be noted that the overestimation of either the annual mean or seasonal rainfall is not exactly proportional to the overestimation of the mean standard deviation, i.e., the strongest mean standard deviations are not necessarily assigned to the wettest models and vice versa.

The RCMs' ensemble mean shows the weakest interannual variability throughout the year. This is a result of the smoothing effect due to the averaging of the monthly outputs of ten RCMs. In general, the ensemble mean of the models tends to overestimate the total variance explained by the seasonality and underestimate the total variance explained by the interannual variability (e.g., Favre et al. 2016). Nevertheless, it has to be noted that the shape of the pattern is correctly reproduced by the ensemble mean with an interannual variability relatively stronger in November (i.e., short rains season).

3.3.2 Interannual variability of seasonal rainfall

The interannual variability of seasonal rainfall over Uganda derived from observational datasets (GPCC, CHIRPS, and CRU), ERA-Interim, ensemble mean, and RCMs is presented in Fig. 6 (see also results for individual models in

Supplementary material Fig. S4). To facilitate the comparison between the models and observations, seasonal time series have been normalized; thus, the long-term mean is equal to 0 and the anomalies are expressed in number of standard deviations. The SRIs have been calculated for the entire year (annual) and also for each season: December–February (dry season), March–May (long rains), June–August (moderate wet season), and September–November (short rains). Next, from the seasonal SRIs, Pearson correlation coefficients between the reference data GPCC and the RCMs, ensemble mean, ERA-Interim, and other observational datasets (CHIRPS and CRU) have been computed and are shown in Table 3. The correlations facilitate a better evaluation of the capacity of models to reproduce the observed interannual variability.

First concerning observational datasets, the correlation coefficients between GPCC and CHIRPS and CRU (Table 3) show relatively high values, in general greater than 0.71 and 0.78, respectively, implying that they are consistent in reproducing the interannual variability pattern across all seasons (see Fig. 6). All of them show the same extremely wet and dry years relative to the 1990–2008 climatology, with small differences in magnitude in some years. It is generally found that CHIRPS shows higher correlation with GPCC than CRU, in terms of interannual variability and for all seasons.

Although ERA-Interim reanalysis shows a temporal pattern relatively similar to the observational datasets (Fig. 6), the annual and seasonal correlation coefficients can vary greatly, ranging between 0.21 and 0.75. The interannual variability of the March–May season (i.e., the long rain season) is poorly correlated with GPCC with r = 0.21 as well as the annual rainfall with r = 0.30 (i.e., those coefficients of correlation are not significant according to a two-sided *t* test). Indeed, ERA-Interim is relatively far from observations during the years 2003, 2004, and 2005, showing thus a strong overestimation especially during the wettest seasons. It has to be reminded that ERA-Interim exhibits a relatively large wet bias and RMSE in the annual and in seasonal mean rainfall compared to the observations (Table 2, Figs. 2m and 4).

Most models including the ensemble mean are consistent in representing the temporal pattern of the June–August and September–November seasons with the exception of MPI-CSC-REMO2009 simulation, which presents low (and not significant) correlation coefficients in both seasons, while BCCR-WRF331 poorly reproduces the temporal pattern (with r = -0.07) of the short rains season. It can be noted that the observed reference dataset GPCC was within the RCMs' range for the 2007 extreme rainfall event during the June– August season, an indication that the models captured well this particular wet year. With regard to the September– November season, there is a large spread among the models. For example, about five RCMs out of ten correctly **Fig. 7** Temporal correlations between ENSO (NINO1.2 (**a**) and NINO3.4 (**b**)) and IOD (**c**) indices and Ugandan rainfall derived from RCMs, ensemble mean, ERA-Interim, GPCC, CHIRPS, and CRU, over the period 1990– 2008. A 3-month sliding window is used to compute the correlations. Horizontal dotted and dashed lines are the 95 and 99% threshold of significance (*t* test)

reproduce the 1997 high rainfall event that was associated with a strong El Niño in phase with a positive IOD (see Fig. S4), while BCCR-WRF331 and CCCma-CanRCM4 show strong dry anomalies.

However, the majority of models fail in reproducing the annual and March–May seasonal interannual variability with generally low correlation coefficients. For instance, MPI-CSC-REMO2009 (r = -0.38) and SMHI-RCA4 (r = 0.09)

simulations present the lowest correlation coefficients in the annual rainfall and March-May season, respectively. Particularly, in 2000, the observed annual and March-May seasonal rainfall was anomalously low and outside of the RCMs' envelop, meaning that all models fail in reproducing this particular dry year. Also, we can note that in 1993 for the annual rainfall, the ensemble mean shows a negative value, outside of the RCMs' range. This is due to the fact that the ensemble mean is computed a priori, and for this specific year, all models show anomalously low values, and some of them, strong negative values (e.g., UQAM-CRCM5; see Fig. S4). Lower rainfall with a relative small spread between models has a consequence, that the year 1993 appears as the driest year of the period according to the ensemble mean, while this is neither the driest year for individual models nor for observations.

Otherwise, the weak correlations during the March– May season may be attributed to the dominance of regional and local factors rather than large-scale ones in the modulation of the seasonal rainfall pattern (Camberlin and Philippon 2002; Indeje et al. 2000). It could also be noted that this season is not homogeneous in terms of interannual variability, since causal factors and teleconnections are markedly different in each month, a point also raised by Nicholson (2017).

The results for the December–February dry season show that the models and the ensemble mean have strong positive and significant correlation coefficients with GPCC (Table 3). All models are consistent in reproducing the interannual pattern of the December–February season with the observed reference dataset GPCC within the RCMs' range (Fig. 6), specifically, the well representation of the rainfall peaks during the DJF 1997/1998 and 2006/2007 El Niño events (Fig. S4). This means that regional and large-scale processes have a dominant role in rainfall variability of the driest season.

It is noteworthy that the interannual variability of the annual rainfall derived from UQAM-CRCM5 is relatively close to observations and outperforms the ensemble mean. This model is also the only one to show significant positive correlation with GPCC, higher than 0.7. More in details, this simulation succeeds in reproducing the interannual variability of rainfall during the half-year period from September to February (i.e., the period including the short rains and the dry seasons). Additionally, the ensemble mean again outperforms ERA-Interim (in all seasons); the improvement is best shown for the two seasons where the models have the lowest skill. The reason why the skill for annual rainfall is generally lower than that of individual seasons likely comes from the fact that it combines the ability of the models to reproduce (i) the interannual variability of seasonal rainfall and (ii) the relative weight of each season in the annual rainfall amount (as shown by some discrepancies in the seasonal rainfall patterns discussed in Section 3).

3.4 Relationship with ENSO and IOD

The interannual variability in rainfall over the East African region is linked with sea surface temperature anomalies over the tropical Pacific and Indian Oceans. Particularly, ENSO (e.g., Ropelewski and Halpert 1987) and IOD (e.g., Saji et al. 1999; Yamagata et al. 2004) are suggested to be dominant drivers of rainfall variability over the region specifically during the short rains season, and this association has been extensively studied (e.g., Mutai et al. 1998; Nicholson and Kim 1997, 2000; Bahaga et al. 2015; Endris et al. 2013, 2016; Indeje et al. 2000). Over Uganda, it has also been shown that the signature of ENSO and IOD is more evident during the short rains than the long rains season (e.g., Camberlin and Philippon 2002; Diro et al. 2011; Endris et al. 2016, 2013; Mutai et al. 1998; Ropelewski and Halpert 1987; Rowell 2013; Saji and Yamagata 2003; Ummenhofer et al. 2009). In addition, the northern summer period in the north of the country also shows a strong relationship with ENSO, although it is reversed compared to that found for the short rains (e.g., Camberlin 1995; Indeje et al. 2000; Ogallo 1988; Phillips and McIntyre 2000). To study the ENSO/IOD-rainfall association at seasonal scale over Uganda, a correlation analysis is applied using SST indices NINO1.2, NINO3.4, and IOD known to present a significant correlation with East African rainfall. Next, we have quantified the significance of the correlation (t test) between seasonal rainfall and SST indices as a means to understand which index relates more with Ugandan rainfall. Results are shown in Fig. 7, where the seasonal correlation coefficients between SST indices and rainfall for the period 1990-2008 are shown for GPCC, CHIRPS, CRU, ERA-Interim, RCMs, and the ensemble mean.

It can be seen that GPCC is significantly correlated with the three SST indices, although not for the whole year. From the end of the short rains to the onset of the dry season, the correlation coefficients are significant, with a better relationship from November to January, with all indices but more specifically with NINO1.2 and IOD. This means that during El Niño (La Niña) as well as positive IOD (negative IOD) phases, more (less) rainfall is received in the short rains season and also in the dry season. Inversely, the sign of correlation tends to reverse from March to April (similar to a study by Camberlin and Philippon 2002 for the ENSO indices), but the relationship is not significant. In May, the correlation with NINO3.4 is again positive and significant, but the correlation is decreasing during the following months and becomes significantly negative in August and September, i.e., the transition period between the long rains and short rains seasons. This period coincides with the annual peak of rainfall over the northern part of the country. As a consequence, La Niña (El Niño) favors rainfall over the north (south) region in August-September (November-January), which is coherent with previous studies (e.g., Phillips and McIntyre 2000).

In general, it can be observed that correlations with NINO1.2 and IOD are higher than those with NINO3.4, but, in all cases, the relationship is not stable through the year. This implies that there is a strong inter- and intraseasonal variation of the signature of NINO1.2, NINO3.4, and IOD indices in the rainfall over Uganda. The other observational datasets also follow the same temporal pattern, but ERA-Interim poorly reproduces the seasonal signature of ENSO, with a too smoothed pattern. For instance, rainfall in ERA-Interim shows a negative correlation with NINO3.4 in AMJ, while the coefficient should be positive according to observational datasets and also the ensemble mean of the ten RCMs. Otherwise, the seasonal signature of ERA-Interim improves with the IOD index.

Concerning the RCMs, it is found out that eight RCMs out of ten (CCCma-CanRCM4, CLMcom-CCLM4-8-17, CNRM-ALADIN52, DMI-HIRHAM5, KNMI-RACMO22T, MOHC-HadRM3P, SMHI-RCA4, and UQAM-CRCM5) are generally able to reproduce the pattern of the seasonal statistical relationship with ENSO and IOD indices, whereas BCCR-WRF311 and MPI-CSC-REMO2009 perform poorly. The MPI-CSC-REMO2009 simulation shows correlations with all indices that are generally too weak and not significant, even if the sign of the coefficient is in general well reproduced throughout the year. The BCCR-WRF311 simulation shows too strong negative correlations with both ENSO indices from August to November and also from September to November with IOD, although the correlations slightly improve. This characteristic is especially visible in October and is associated with a strong wet bias over the southwestern part of the country (see Supplementary material, Fig. S3) and with an overestimation of the interannual variability for this month specifically (see Fig. 5). Finally, it is worth noting that UQAM-CRCM5 outperforms any individual model in its representation of the seasonal signature of ENSO and IOD with rainfall. The ensemble mean of the ten RCMs correctly reproduces the statistical links with both ENSO and IOD indices (Fig. 7).

It is worth noting that IOD is not statistically independent of ENSO over the period 1990–2008 considered. To demonstrate this, we have plotted the ENSO indices over the Pacific Ocean against the IOD index over the Indian Ocean (Fig. S5). We further note that the interannual variability of IOD is significantly positively correlated with NINO1.2 and NINO3.4 from September to January/ February (more strongly with NINO1.2; Table S1). Indeed, over our study period, most of El Niño phases co-occurred with positive anomalies of IOD (e.g., 1994– 1995, 1997–1998, 2006–2007), and inversely most La Niña phases co-occurred with negative anomalies of IOD (e.g., 1998–1999, 2000–2001, 2005–2006). This feature is more marked for November and December months.

4 Summary and conclusion

Improving the understanding and predictability of rainfall is of high importance for Uganda, whose economy is mainly based on rainfed agriculture and therefore vulnerable to climate variability and climate change. Phillips and McIntyre (2000) pointed out that the variation in rainfall patterns from the north to the south is a key factor that dictates the cropping systems, including the choice of crop and planting time.

In this study, the CORDEX RCMs have been analyzed for their ability to capture and characterize present climate (1990– 2008) rainfall patterns over Uganda. Results from ten different RCMs with horizontal resolution of 0.44°, forced by ERA-Interim for the period 1989–2008, are compared against three observational datasets: the Global Precipitation Climatology Centre (GPCCv7), the University of East Anglia Climatic Research unit (CRU TS3.10), and the Climate Hazards Group InfraRed Rainfall (CHIRPS) datasets, as well as the ERA-Interim reanalysis. Performances of the individual models and the ensemble mean are analyzed both at annual and seasonal time scales, by using several metrics. We have also investigated the rainfall response to the ENSO and IOD signal.

It is found that most models underestimate the annual mean rainfall over the country. This is particularly the case for MPI-CSC-REMO2009 and CLMcom-CCLM4-8-17. The quasisystematic dry biases, generally found over areas of lower altitude especially over the west shores of Lake Victoria, may be associated with moisture outflow in that region. Indeed, the spatial distribution of annual mean rainfall biases tends to follow the terrain elevation in the region, a feature that is satisfactorily reproduced by four models (SMHI-RCA4, DMI-HIRHAM5, BCCR-WRF331, and CNRM-ALADIN52). This has also been noted by Favre et al. (2016) over South Africa. With regard to seasonality, the models capture properly the unimodal and bimodal distributions of the annual cycle over the north and south parts of the domain, respectively. However, rainfall is underestimated by most models from March to May (i.e., the main rainy season), which is the most important rainfall season for the agricultural activities in Uganda. Notably, CORDEX RCMs have been found to underestimate March-May seasonal rainfall also over Southern Africa (e.g., Kalognomou et al. 2013).

Most models tend to underestimate the magnitude of the interannual variability of rainfall over Uganda, in comparison with GPCC. Nevertheless, they properly reproduce the relatively stronger variance during the short rains season better than during the long rains season. The ensemble mean shows the weakest interannual variability throughout the year, due to the smoothing effect of the average of the ten RCMs' results. On the other hand, there are differences in models' performance in the simulation of the interannual variability of seasonal rainfall over the region. For instance, all models (including the ensemble mean) capture the interannual pattern of the December–February season reasonably well as compared to other seasons. Particularly, it is observed that wetter conditions during this particular season occur during El Niño events, an indication that as climate change is expected to increase the frequency of extreme El Niño events (Cai et al. 2014), the frequency of unusually wet December–February seasons is also likely to increase in magnitude. In fact, earlier studies (Nimusiima et al. 2014; Shongwe et al. 2011; Vizy and Cook 2012) showed that the December–February season has experienced an increasing trend in rainfall amounts that may be associated with signals of climate change.

The capability of CORDEX RCMs to capture the seasonal rainfall anomalies related to ENSO and IOD was also assessed. Uganda rainfall shows seasonally contrasted correlations with ENSO and IOD, and all models except BCCR-WRF311 and MPI-CSC-REMO2009 are found to reproduce the pattern of the seasonal signature with both ENSO and IOD indices. UQAM-CRCM5 generally performs better than the other models and, in some cases, comparably to the ensemble mean.

Some general concluding remarks can be drawn from this study:

- 1. Some models (e.g., CLMCom-CCLM4-8-17 and MPI-CSC-REMO2009) perform particularly poorly in representing the rainfall patterns over Uganda. This may be due to a combination of (a) resolution (which may be still to coarse to adequately reproduce all the effects related to complex topography; for Uganda, this is probably so in the western part of the country where major relief features (e.g., Albertine Rift, Rwenzori ranges) are likely not fully resolved at the resolution of the CORDEX models) and (b) physical parameterization, which may play a relevant role. For instance, Dosio and Panitz (2016) showed that when driven by different GCMs, precipitation trends simulated by CLMCom-CCLM4-8-17 and the GCMs show opposite signs, with CCLM showing a significant reduction in precipitation. This feature, not limited to CCLM, was revealed for other RCMs and was related to the different parameterization of, e.g., the hydrological cycle and, in general, the different response to the soil moisture/precipitation feedbacks. For example, Breil et al. (2017) demonstrated the importance of soil vegetation-atmosphere (SVAT) interaction for a more realistic spatial rainfall distribution in the Central Sahel. Therefore, more work is necessary to fully understand the mechanisms governing precipitation over (or part of) Africa (e.g., land-atmosphere interaction) and how models simulate them.
- RCMs are generally able to well reproduce the influence of large-scale climatic modes such as ENSO and IOD, but some of them present difficulties concerning regional and

local processes influencing precipitation such as the ITCZ, orographic forcing, and land-lake breezes, yet these are key drivers for Ugandan rainfall. Studies by Anyah et al. (2006), Thiery et al. (2015), and Williams et al. (2015) underlined the part played by the East African lakes in general and Lake Victoria in particular in the regional climate conditions. For Uganda, there is actually a wide range between the RCMs in the rainfall amounts they simulate over Lake Victoria and along its shores.

- 3. Although there are some intermodel differences, the ensemble mean simulates the rainfall adequately with a minor or major improvement (depending on the rainfall season considered) upon the driving model (ERA-Interim) and can therefore be useful for the assessment of future climate projections for the region.
- 4. Lastly, it must be noted that evaluating RCMs when driven by ERA-Interim only gives a flavor of how good they are when driven by "perfect" boundary conditions. However, for climate change simulations, RCMs will be driven by GCMs, which will add their own biases on top of those of the RCMs. Therefore, performing analysis of the evaluation of the RCMs driven by GCMs is essential in order to assess whether RCMs are able to add value to the driving GCMs.

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