Atmospheric Research 202 (2018) 205–218

Contents lists available at ScienceDirect

Atmospheric Research

journal homepage: www.elsevier.com/locate/atmosres

Characterization of the Sahelian-Sudan rainfall based on observations and regional climate models

Abubakr A.M. Salih[a,d,*], Nadir Ahmed Elagib[b], Michael Tjernström[a,d], Qiong Zhang[c,d]

[a] Department of Meteorology, Stockholm University, Stockholm, Sweden
[b] Institute for Technology and Resources Management in the Tropics and Subtropics (ITT), Technische Hochschule Köln, 50679 Cologne, Germany
[c] Department of Physical Geography, Stockholm University, Stockholm, Sweden
[d] Bolin Centre for Climate Research, Stockholm University, Stockholm, Sweden

ARTICLE INFO

Keywords:
Regional modeling
Climate model evaluation
Precipitation
Sahel
Rain-day analysis

ABSTRACT

The African Sahel region is known to be highly vulnerable to climate variability and change. We analyze rainfall in the Sahelian Sudan in terms of distribution of rain-days and amounts, and examine whether regional climate models can capture these rainfall features. Three regional models namely, Regional Model (REMO), Rossby Center Atmospheric Model (RCA) and Regional Climate Model (RegCM4), are evaluated against gridded observations (Climate Research Unit, Tropical Rainfall Measuring Mission, and ERA-interim reanalysis) and rain-gauge data from six arid and semi-arid weather stations across Sahelian Sudan over the period 1989 to 2008. Most of the observed rain-days are characterized by weak (0.1–1.0 mm/day) to moderate (> 1.0–10.0 mm/day) rainfall, with average frequencies of 18.5% and 48.0% of the total annual rain-days, respectively. Although very strong rainfall events (> 30.0 mm/day) occur rarely, they account for a large fraction of the total annual rainfall (28–42% across the stations). The performance of the models varies both spatially and temporally. RegCM4 most closely reproduces the observed annual rainfall cycle, especially for the more arid locations, but all of the three models fail to capture the strong rainfall events and hence underestimate its contribution to the total annual number of rain-days and rainfall amount. However, excessive moderate rainfall compensates this underestimation in the models in an annual average sense. The present study uncovers some of the models' limitations in skillfully reproducing the observed climate over dry regions, will aid model users in recognizing the uncertainties in the model output and will help climate and hydrological modeling communities in improving models.

1. Introduction

Most studies of Sahel rainfall have focused on annual, seasonal, monthly and daily time scales (Eldredge et al., 1988; L'Hote et al., 2002; Dai et al., 2004; Nicholson, 2005; Lebel and Ali, 2009; Fontaine et al., 2011; Elagib and Elhag, 2011; 201; Diatta and Fink, 2014). However, other rainfall properties are of vital importance for hydrology, agriculture, urban planning and management of natural hazards. Among these, the number of rain-days, the rainfall intensity (amount per time unit) especially for extreme events and the distribution of rain-days over the season can be noted. Successful rain-fed agricultural and water-resource systems, for instance, require detailed information about the nature of rainfall over the season such as the onset of rainy season, the spatial and temporal distribution of rain as well as its intra-to-inter-annual variability. A few attempts have been made to investigate such rainfall characteristics over the Sahel region (see e.g. Seleshi and Zanke, 2004; Tilahun, 2006; Elagib, 2010b; Sulieman and Elagib, 2012; Sanogo et al., 2015).

Sulieman and Elagib (2012) found that around 61% of the annual rainfall in El Gedaref, Sudan (14° 02′ N, 35° 24′ E) in 2009 was recorded during only 7 days, each with a rainfall > 30 mm/day. This kind of concentrated rainfall is less useful for rain-fed agriculture, compared to when the corresponding amount is distributed over a reasonably longer time. If severe rainfall (> 30 mm/day) coincides with the early stage of the growing season when the soil is dry and bare, it likely generates large overland flow (runoff), causing erosion of the fertile top layer of the soil (e.g. Wickens, 1997; Taddese, 2001; El Tahir et al., 2010; Elagib, 2011). Rainfall characteristics are also indicative of the underlying mechanism, i.e. whether it is due to large-scale circulation (slowly moving weather systems) or to local convection. Examination of these features can provide insights into the fluctuations of forcing and the mechanisms that give rise to natural hazards, such as droughts and floods. Knowledge of this behavior is very useful, for instance, for modeling activities as it can reveal model deficiencies and limitations.

* Corresponding author at: IGAD Climate Prediction and Application Center, P.O. Box 10304, 100 Nairobi, Kenya.
E-mail address: abubakr@misu.su.se (A.M. Salih).

https://doi.org/10.1016/j.atmosres.2017.12.001
Received 23 March 2017; Received in revised form 19 November 2017; Accepted 2 December 2017
Available online 05 December 2017
0169-8095/

In this regard, validation of satellite-based precipitation datasets in ground data-sparse areas, such as tropical Africa, for studies of sub-daily (diurnal cycle) is useful (Pfeifroth et al., 2016).

The objective of the present paper is to analyze these rainfall characteristics in greater detail, with a focus on the Sudanese Sahel. The Sahel zone of Sudan, stretching from 10° to 15°N and from 22° to 36°E, is classified as arid to semi-arid. This region relies on rainfall as a source of water for different purposes. Farming practiced away from the Nile basin is largely dependent on rainfall for its irrigation. Similar to the entire African Sahel, from the Ethiopian plateau in the east to the coast of the Atlantic Ocean in the west, Sahelian Sudan has suffered from drought conditions during the last four decades, manifested by a reduction in annual rainfall and increasing temperatures (see e.g. Hulme, 1990; Eltahir, 1992; Elagib, 2010a; Elagib and Elhag, 2011). Consequently, these drought conditions have proved to be highly deleterious to agricultural yield (Elagib, 2014). Regions having such limited water resources are foreseen to be highly vulnerable to the impacts of climate change and variability (IPCC, 2007b), especially that they are highly dependent on rain-fed agriculture for the livelihood and food security of the population (Batterbury and Warren, 2001; Balogun, 2011).

In the present study we evaluate the ability of three regional climate models (RCMs) in simulating detailed features of Sahelian-Sudan rainfall, comparing model output to observations from both gauging stations and gridded precipitation products. While the hypothesis herein is that RCM grid-averaged data are expected to differ from rain-gauge point observations, there is a need to document these differences if the model output is to be useful for local applications (Rivington et al., 2006). Hence, the contributions from the present study can be summarized as falling within two main themes. First, an evaluation of three RCMs is carried out for one of the least studied regions, the Sahelian zone of Sudan. This region can be seen as linking the western African Sahel with East Africa as well as with the Indian Ocean. Second, the study addresses novel evaluation approaches of RCMs and the Tropical Rainfall Measuring Mission (TRMM), by comparison to point observations on rarely examined metrics: (1) the distribution of rain-days, characterized according to rain amount per day, (2) the contribution of these rain-day categories to the total annual rainfall, (3) the distribution of rain-days over the months and (4) the monthly contribution to the total annual rainfall.

A short overview of regional climate models is given in Section 2, followed by a description of data and methods in Section 3. The results of the analysis are presented in Section 4, followed by a discussion in Section 5. Finally, the conclusions are given in Section 6.

2. Overview of regional climate models (RCMs)

Global Climate Models (GCMs) are reasonably reliable in describing the response of the climate system to various forcings, but usually have too coarse spatial resolution to provide the detailed regional-scale information needed for example for hydrological applications, water-resource management or for agricultural or urban planning. A Regional Climate Model (RCM) encompasses a limited area and can therefore provide higher resolution at a reasonable computational cost. It relies, however, on lateral boundary information from a global model. RCMs have been developed as a dynamic downscaling tool, and have been widely used to study past, present and future climate on different time and space scales (e.g. Hudson and Jones, 2002; Liang et al., 2006; Sylla et al., 2010; Tang et al., 2011).

Recently, the term "added value", referring to the additional information provided by the RCMs, has prevailed among RCMs users (Rummukainen, 2010; Feser et al., 2011), while recognizing that some systematic errors from the driving global model are inherited in the RCM. RCMs have also been used in sensitivity studies to examine the response of regional climate to physical processes and changes in local conditions (e.g. Moufouma-Okia and Rowell, 2010; Salih et al., 2013; Liu et al., 2015). Thus, the fidelity of models in reproducing the observed regional climate has received a great attention from the scientific community. Many statistical techniques have been applied to assess how well regional and global models capture the observed climate. Probability density functions (e.g. Perkins et al., 2007; Schoetter et al., 2012), mean and root mean square errors (see e.g. Christensen et al., 1997; Segele et al., 2009), correlations (Small et al., 1999) and Taylor diagrams (Taylor, 2001) are examples of techniques used to evaluate the model performance. Most assessments focus on how well the models reproduce the mean annual and diurnal cycles, variability, and the spatial pattern of the observed climate and on how much uncertainty is involved in these predictions.

Model-simulated precipitation is usually evaluated against observation-based gridded data such as the Climate Research Unit (CRU) datasets (New et al., 2000) and the Global Precipitation Climatology Project (GPCP; Huffman et al., 1997). Reanalysis datasets, such as those developed by National Center for Environmental Prediction (NCEP) (Kalnay et al., 1996; Kistler et al., 2001) and by the European Center for Medium Range Weather Forecasts (ECMWF) (e.g. ERA-Interim; Dee et al., 2011), are also frequently used to evaluate simulated precipitation and the associated atmospheric circulation. However, there are issues that should be borne in mind when using either gridded or reanalyzed precipitation datasets. Gridded observational data are a combination of station records and statistical interpolation; one might therefore expect some attenuation of local climate signals by the interpolation (Schoof and Pryor, 2003; Szczypta et al., 2011). In reanalysis, precipitation is usually not assimilated but comes solely from the model forecast. This is a sub-grid scale process that needs parameterization in the model. Therefore, the quality of reanalyzed precipitation depends not only on the observational constrains, the assimilation technique and the quality of the observations, both those assimilated and those used as prescribed forcing (e.g. Sea Surface Temperature, SST), but also depends on the physical parameterizations in the model.

Zhang et al. (2013) showed that there is a degree of spatial mismatch between the reanalysis data and observations - both in climatology and variability - over Africa south of the equator. Evaluation efforts also vary according to temporal coverage, climate variables and regions of interest. For instance, models are known to simulate the surface temperature more accurately than precipitation (IPCC, 2007a). Kendon et al. (2012) state that: "*if rainfall is more realistic in a climate model, there is greater confidence in its projections of future change*". Broadly speaking, a detailed evaluation of model performance versus surface observations for Africa is rarely found in the literature, probably due to the "*currently limited availability of long and high-quality surface instrumental climate records*" (Washington et al., 2006; Brunet and Jones, 2011).

3. Data and methods

3.1. Observational data

In the present study, a large body of data from several sources is used. Daily rainfall observed at six weather stations during the period extending from January 1, 1989 to December 31, 2008 was obtained from the Sudan Meteorological Authority. The arid and semi-arid climatic zones of Sahelian Sudan are represented by three stations each. The arid stations are Shambat (15.67°N, 32.53°E), Wad Medani (14.4°N, 33.48°E), and Kosti (13.17°, 32.67°E) whereas the semi-arid ones are El Gedaref (14.03°N, 35.40°E), Kadugli (11.0°N, 29.72°E) and Nyala (12.07°N, 24.88°E). The locations of the stations are shown in Fig. 1. None of these datasets had missing observations during the study period.

Three different gridded rainfall datasets were also used: an updated version of CRU TS3.10 (Harris et al., 2014), ERA-interim and TRMM (TRMM 3B42 version 6, Huffman et al., 2007). These three datasets vary substantially in the way they are constructed and also in temporal

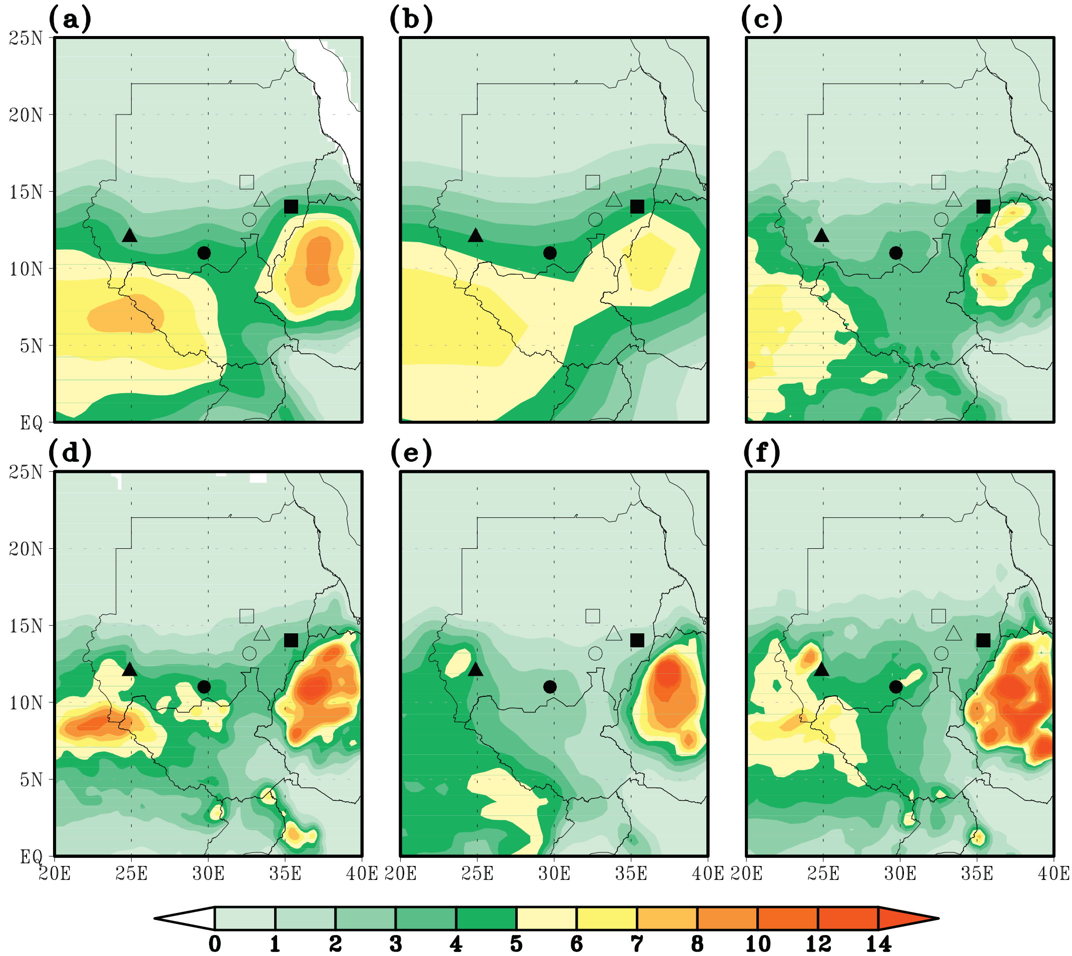

Fig. 1. Average rainfall in mm/day during the main rainy months June to September (for the period 1989–2008), from CRU (a), ERA-interim (b), TRMM (c), RegCM4 (d), REMO and (e) RCA (f). Three arid stations are Shambat, Wad Medani and Kosti, represented by an open square, triangle and circle, respectively. The semi arid stations El Gedaref, Nyala and Kadugli are show by a filled square, triangle and circle, respectively.

and spatial resolution. CRU provide monthly mean rainfall at a resolution of 0.5° × 0.5°, obtained through statistical interpolation of all available rain-gauge data. CRU could thus be said to be the closest to the actual direct observations, however, sacrificing temporal resolution and adding some uncertainty, especially in data-sparse regions. ERA-interim data are used at 0.5° × 0.5° where the precipitation is a product from the ECMWF forecast model. Short model forecasts are initialized by assimilated data where the best model and observational information is optimized; model results from a previous short forecast are corrected using observations. Precipitation is not assimilated, but is a model product. Since everything in a model is being connected, the model precipitation is consistent with other model variables, which are assimilated. Both the CRU and ERA-interim data are available for the whole study period (1989 through 2008). In contrast, TRMM has higher spatial and temporal resolution, but is only available for a shorter period, viz. from 1998 onward. TRMM is a daily-rainfall product that combines rain-gauge and satellite data on a 0.25° × 0.25° grid. Hence, TRMM is an observation product, but only indirectly. The satellite does not measure precipitation directly but measures radiation and instead relies on a retrieval algorithm.

In the following sections, the gridded datasets are used to evaluate the general performance of the models in capturing the spatial distribution of rainfall across the region. The station data, on the other hand, are used to evaluate rainfall features on a daily scale. Comparing model output, which is inherently area-averaged, with single-point observations is an unavoidable problem. There are however valid justifications for using point observations to evaluate model output at a grid resolution of 50 × 50 km grid resolution. The argument here is that the gridded data, which are area-averaged, are conceptually closer to what is simulated by a model, while precipitation in reality often occurs locally with large spatial variability. Although rainfall is difficult to measure it is, however, most accurately captured at local observation stations. Therefore, a true comparison of models to observations must at some point incorporate direct observations of precipitation; such observations are only available from single-point stations. Local stations are also better at capturing precipitation extremes. It all comes down to assessing the representativity of the single-point station data. Therefore, the representativity of the station data are also investigated using TRMM, for both the annual cycle and the magnitude of the rainfall. TRMM data are also used alongside the station data for the analysis of more detailed characteristics of the rainfall.

3.2. Models

The RCMs used in this evaluation include the Regional Climate Model - version 4 (RegCM4) from the International Center for Theoretical Physics in Trieste, the Regional Model (REMO) from the Max Planck Institute for Meteorology, and the Rossby Center regional Atmospheric model (RCA) from the Swedish Meteorological and Hydrological Institute. All three models are hydrostatic and were run at a similar horizontal resolution over similar domains. RegCM4 solves the primitive equations of the atmospheric motion using finite difference over a terrain-following vertical sigma-pressure coordinate system with 18 vertical levels. In contrast, both REMO and RCA utilize semi-

Table 1
Model specifications and parameterizations.

Model	Vertical coordinates/# of levels	Advection	Convective scheme	Radiation scheme	Surface scheme
RegCM4	Sigma/18	Eulerian	Grell et al. (1994) Fritsch and Chappell (1980)	Kiehl et al. (1996)	BATS1E Dickinson et al. (1993)
REMO	Hybrid/27	Semi-Lagrangian	Tiedtke (1989)	Morcrette et al. (1986) Giorgetta and Wild (1995)	Hagemann (2002) Rechid et al. (2009)
RCA	Hybrid/40	Semi-Lagrangian	Kain and Fritsch (1990, 1993)	Savijärvi (1990) Sass et al. (1994)	Samuelsson et al. (2006)

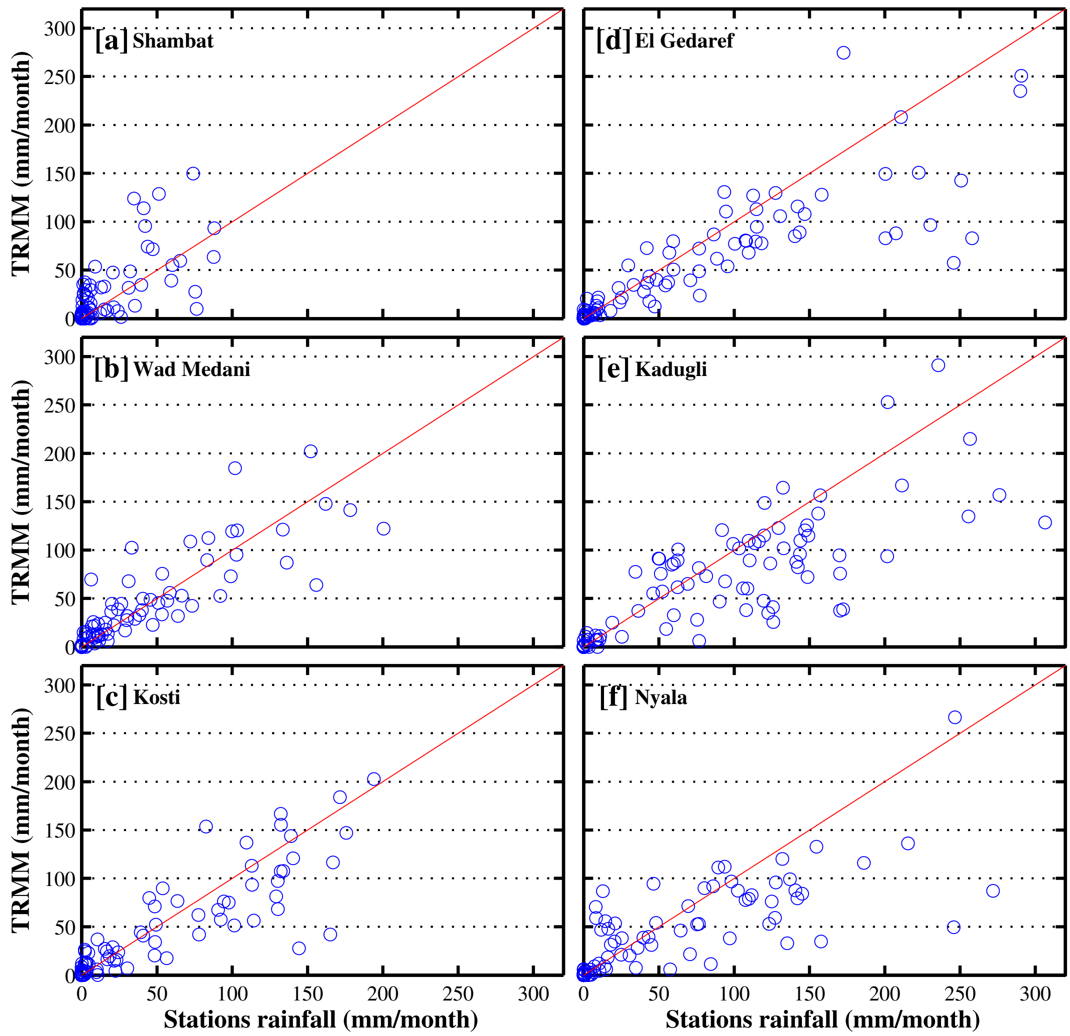

Fig. 2. Scatter plots of TRMM monthly rainfall against station data for 1998–2008. The red line shows the hypothetical 1:1 relation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Statistics of the correlation between the stations and TRMM datasets. The linear regression form is TRMM = a + b × Station.

Station	Kendall tau test		Linear regression					
	tau	p	a	p	b	p	R^2	p
Arid stations								
Shambat	0.717	0.00	4.029	0.030	1.050	0.001	0.550	0.00
Wad Medani	0.856	0.00	4.167	0.290	0.858	0.00	0.790	0.00
Kosti	0.823	0.00	2.672	0.200	0.801	0.00	0.806	0.00
Semi-arid stations								
El Gedaref	0.865	0.00	4.151	0.123	0.679	0.00	0.831	0.00
Kadugli	0.780	0.00	3.403	0.120	0.036	0.00	0.733	0.00
Nyala	0.783	0.00	6.629	0.010	0.576	0.00	0.662	0.00

Lagrangian advection schemes and hybrid vertical coordinates with 27 and 40 vertical levels, respectively. For more details regarding these models, the reader is referred to Giorgi et al. (2012) for RegCM4, Jacob (2001) for REMO and Samuelsson et al. (2011) for RCA. Some information on the schemes and parameterizations used in the three RCMs are provided in Table 1.

The setup of the model simulations follows the Coordinated Regional Climate Downscaling Experiment (CORDEX) as discussed by Jones et al. (2011) for the African domain. All three models have a horizontal resolution of ~50 km and use the same lateral boundary forcing from the ERA-interim reanalysis. Dynamic and thermodynamic fields at the lateral boundaries are updated 6-hourly. The domain of the RegCM4 experiment stretches from 22.75°W to 63.27°E and from 37.69°S to 40.85°N, the REMO domain extends from 28.16°W to

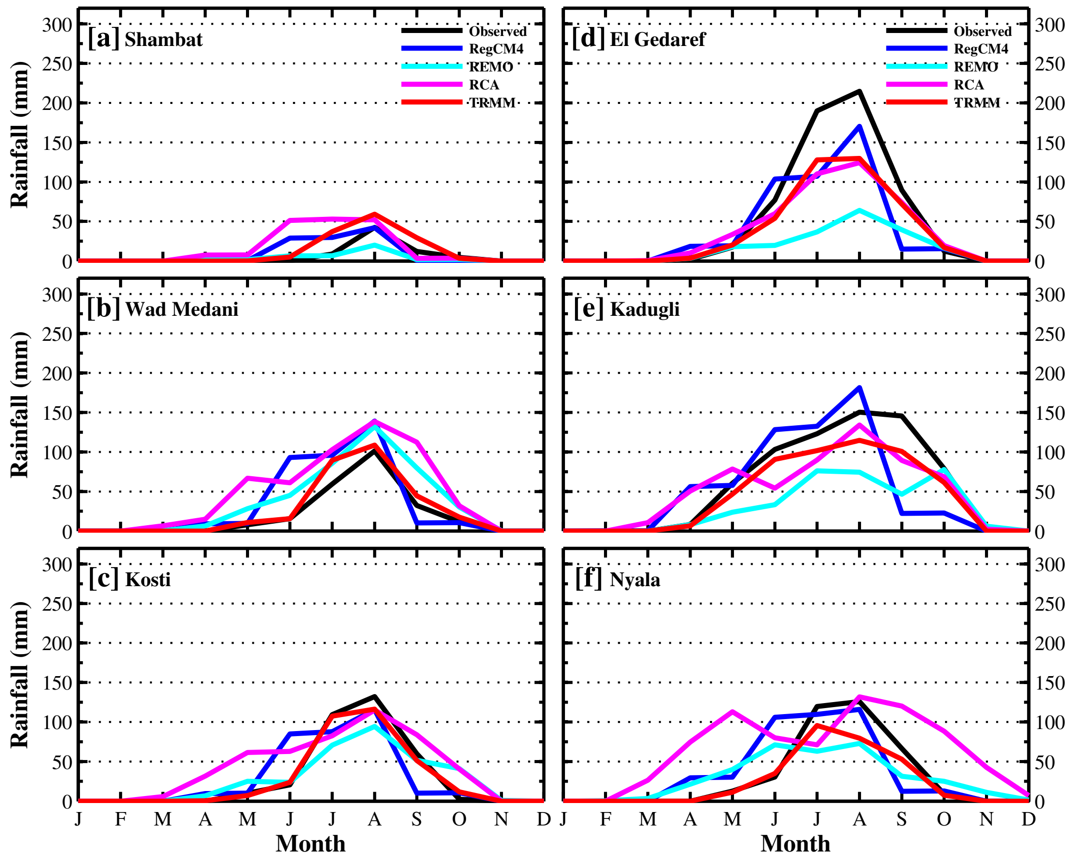

Fig. 3. Annual cycle of monthly rainfall using RegCM4, RCA, REMO and TRMM dataset.

66.88°E and from 49.28°S to 45.76°N, whereas RCA has a domain stretching from 24.64.8°W to 66.26°E and from 45.76°S to 42.24°N. In the present study, all plots will only display a smaller portion of the domain, centered over Sudan.

3.3. Methods of rainfall analysis

Rainfall is grouped into five classes as described by Elagib (2010b). Weak (W) is defined as 0.1 to 1.0 mm/day, moderate (M) is > 1.0 to 10.0 mm/day, moderately strong (MS) > 10.0 to 20.0 mm/day, strong (S) > 20.0 to 30.0 mm/day and very strong (VS) > 30.0 mm/day. The analysis is focused on four features:

- The number of rain-days in each class relative to the total annual rain-days.
- The number of rain-days in each month relative to the total annual rain-days.
- The relative contribution of each rainfall class to the total annual rainfall.
- The relative contribution of each month to the total annual rainfall.

The distribution of rain-days is considered only for the wet months, extending from 1 April to 31 October. This detailed analysis was performed for the station and TRMM datasets but not for CRU and ERA-interim, since daily data are not available for CRU, and since ERA-interim showed a tendency to underestimates the daily rainfall over the region, as shown in Section 4.1.

Since the rainfall probability distribution for such a region is skewed and cannot be described by a normal distribution (e.g. Tilahun, 2006; Abtew et al., 2009), the median is used as a statistical measure rather than the mean to avoid undue influence of outliers. For the same reason, the non-parametric Wilcoxon-Manny rank sum test, which does not assume any particular distribution of the data (Ibrahim et al., 2012), is used to examine whether the difference between the model output and observations is statistically significant or not. This test examines the difference in ranking of observations between the two datasets. We use a test in which the null hypothesis is that the two datasets are from the same continuous distribution with equal median.

Our analysis deals with the nature of model errors by examining their probability density functions (PDF). The relative PDF of the errors in the number of rain-days and the monthly rainfall amount (for April to October only) was established for the whole study period. It is expected that the nature of the constructed PDF will make it possible to discriminate between random and systematic errors. Precipitation in the models is generated by two components: resolvable, large-scale processes, such as large-scale ascent associated with synoptic scale weather events (large-scale precipitation) and by convective ascent, which has to be accounted for by the convection parameterization (convective precipitation). Following the analysis of the nature of errors, possible sources of these errors can be explored.

4. Results

4.1. The spatial distribution of rainfall

Fig. 1 shows the spatial distribution of average daily rainfall during the main monsoon period June through September from CRU, ERA-interim, TRMM, RegCM4, REMO and RCA. All the gridded data and the model results agree on the general regional rainfall pattern, but they differ in details. There are two areas of larger precipitation; one larger in southwestern Sudan and Chad and one smaller to the east, over the Ethiopian highlands. All three gridded data sets feature both of these, but with large differences. In CRU and TRMM the relative magnitudes between these two areas are similar, whereas the absolute values are

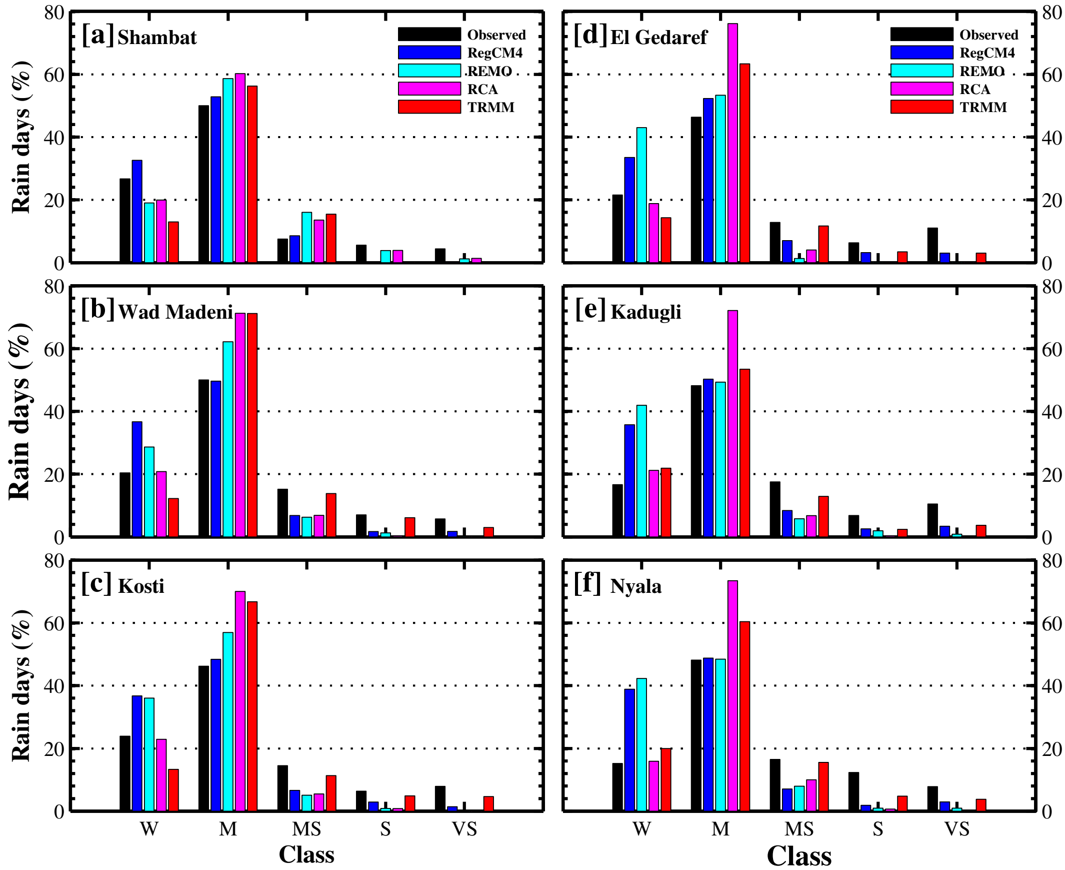

Fig. 4. Median frequency of rain-days for rainfall classes expressed in percentage of the total annual rain-days. See the text for the definition of rain classes.

higher in CRU than in TRMM. ERA-Interim is different; not only is the precipitation in general lower but it also has much lower precipitation in the southwestern region than over the Ethiopian highlands. Both CRU and TRMM show higher rainfall amount over Sahelian Sudan than ERA-interim. Nikulin et al. (2012) found that TRMM underestimates the rainfall compared to CRU and GPCP, consistent with these results, yet it provides a better estimate than ERA-interim. There is a positive rainfall gradient from north to south, with 0–1 mm/day in most of the region north of 16°N, and reaching 5–7 mm/day south of 10°N. While the magnitudes differ, all gridded data captures this gradient. It is also worth noting how similar the large-scale patterns are in both CRU and TRMM, although the latter has a much higher spatial resolution. These results also illustrate the problem with the gridded precipitation data; asking the question on how much precipitation there is, obviously the results differ depending on which data source one chooses.

In the RCMs, the area of the southwestern rainfall maximum is smaller than in the gridded data, with the possible exception for ERA-Interim where the values on the other hand are very low. The RCMs also capture rainfall maxima associated with the topography in the Ethiopian highland (~4.5 km above mean sea level a.m.s.l.) and in Jebel Marra (~2 km a.m.s.l.) in western Sudan. The topographical effects are more pronounced in the regional models, giving annual averages of 12–14 mm/day, compared to the gridded data with 7–10 mm/day. Rainfall in elevated regions is difficult to capture by the models, due to numerical and resolution problems, but also by the gridded datasets due to lack of observations. All models are forced by ERA-interim reanalysis; hence, any differences between them must have to do with how the precipitation and dynamics work in the three different models. Given the uncertainty in the actual values and patterns of precipitation discussed above, it appears that especially RegCM4 and RCA provide a more realistic spatial distribution of the rainfall than ERA-interim; also see the discussion on "added values" above and in Rummukainen (2010) and Feser et al. (2011).

4.2. Annual cycle and correlation of rainfall

Fig. 2 shows a scatter plot of the monthly rain-gauge and TRMM data for the six stations. In general, the agreement between the two distinct sets is good although some systematic differences appear. For example, there is a clear tendency for TRMM to underestimate the highest values for most of the stations. Table 2 shows the statistics of the correlation between the stations and TRMM datasets. The Kendall tau rank correlation test and linear regression show a strong positive correlation between the two datasets. The average correlation statistic as per the Kendall tau test is 0.8. A mixed tendency is indicated for both groups of the stations by the determination coefficient, R^2. On average, the station data explain 72 and 74% of the variations in the TRMM data for the arid and semi-arid stations, respectively. However, not unexpectedly, substantial scatter characterizes the station with the lowest rainfall, i.e. Shambat, with R^2 of only 0.55. Therefore, it can be concluded that TRMM corresponds somewhat to both the arid and semi-arid station data, except in the extreme arid part; however, more analysis is needed to test and calibrate this relationship.

Fig. 3 assesses TRMM and RCM results in reproducing the annual cycle of rainfall over the six selected stations. For the two arid stations at Wad Medani and Kosti (Fig. 3b and c, respectively) there is a good agreement between TRMM and the stations data, while at Shambat (Fig. 3a), TRMM overestimate precipitation during the peak season (July through September). In the semi-arid region, there is a pronounced underestimation of the rainfall amount and a systematic underestimation of the peak of the annual cycle. However, the TRMM and the station data agree on the lengths of the rainy season and on the rainy months.

The performance of the models varies from one station to another. A

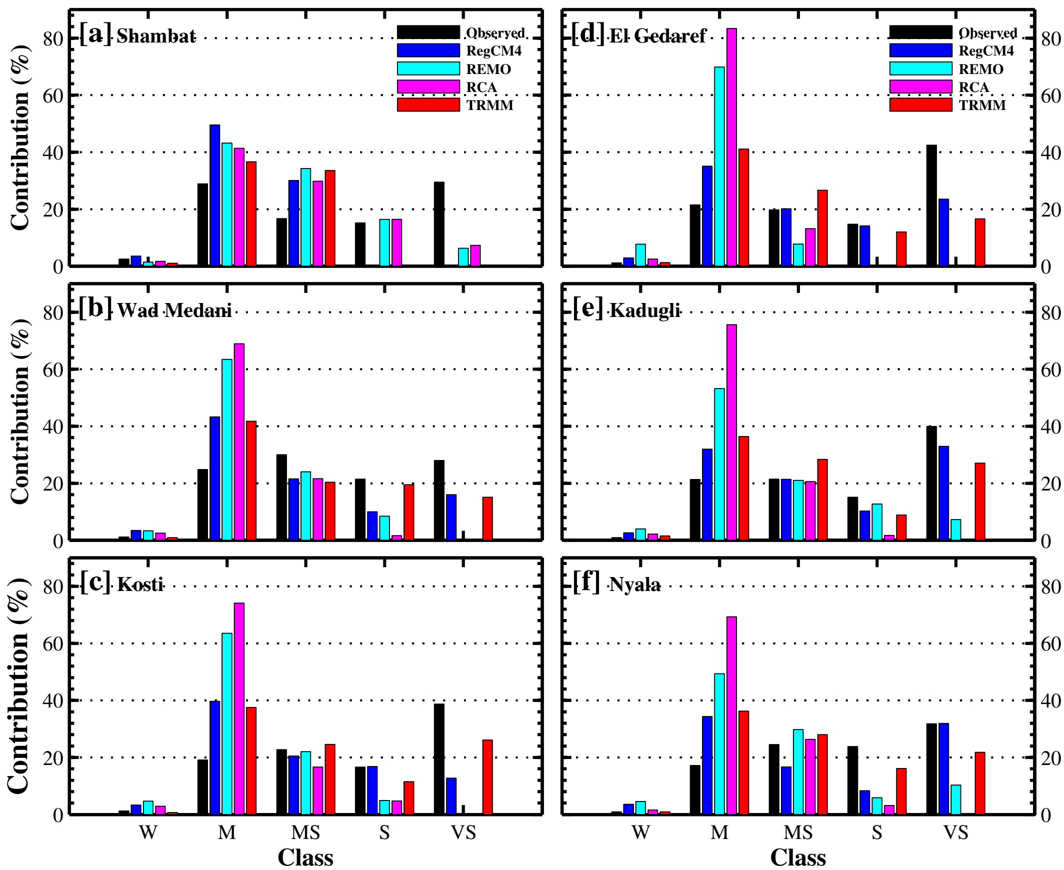

Fig. 5. Median contribution of rain-day classes to total amount of rainfall.

clear disagreement with observations in the seasonality of rainfall is demonstrated by RCA, displaying a strange double-peak behavior for four of the six stations, especially pronounced at Nyala (Fig. 3f). The two peaks consistently occur in May and August. However, the observations show August as the single wettest month, whereas May is normally a month with little rain. RCA also tends to display a prolonged rainy season. While REMO also tends to have an extended rainy season, it has less rainfall than RCA. REMO also underestimates the monthly magnitude of the rainfall for Shambat, Kosti, El Gedaref, Kadugli and Nyala (Fig. 3a, c, d, e and f, respectively). Although the observed values at these stations vary between 130 and 200 mm (excluding Shambat), REMO's peak stays well below 100 mm.

For the timing of peak of the rainy season, RegCM4 agrees with the observational data for most of the stations, but less so regarding the amount of rainfall. The model overestimates the rainfall at the start of the rainy season (June) and underestimates it at the end of the season, for all the stations. The rainfall in RegCM4 drops sharply in September while the observed precipitation continues to be large until October. In general, RegCM4 simulates the observed annual cycles reasonably well, except at El Gedaref (Fig. 3d) and Kadugli (Fig. 3e) where it underestimates the rainy-season peak by about 16% and 13%, respectively.

4.3. Frequency of rain-days within classes

Fig. 4 compares the median of the rain-day frequencies within each of the five precipitation classes, for the models and the TRMM and station data. Several common features characterizing the observed rainfall can be noted. First, most of the rain-days occur in the M class (> 1.0–10.0 mm/day), accounting for between 46% and 50% of the total number of rain-days. Second, the W class accounts for between 15% and 22% of the rain-days. The prevalence of days with light rain can be attributed to rainfall suppression by atmospheric dust frequently occurring over the dry region (Hui et al., 2008; Elagib, 2010b). Third, the least frequent type of rain-days occurs in the VS class. Overall, the difference between the TRMM data and the station observations is most pronounced in the M and W classes.

Starting with the dominant M class, RCA yields an overestimation across the region, by between 10 and 30%, while REMO's performance is very good within the semi-arid zone, but yields an overestimation for the arid stations. RegCM4 shows the best performance among the models, almost exactly matching the observations at all the stations. For the weaker W-class, RCA shows a reasonable performance while REMO and RegCM4 overestimate the frequency of rain days for all stations, except at Shambat (Fig. 4a), where there is slightly underestimation in REMO. For the stronger MS and S classes, both REMO and RCA underestimate the rain-days for all the stations except Shambat where they slightly overestimate the rain-days in the MS class; these two models have no rain days in the S-class at most of the stations. In contrast, RegCM4 results are closer to the observations, but still do not capture the frequency for MS-class and also deviate considerably for the S class. Finally, none of the models reproduces the observed frequency of rain-days in the VS class.

In summary, all models have difficulties reproducing the few number of days with strong or very strong precipitations, i.e. for the S and VS classes, but they also underestimate the MS days. They generally compensate for this by having more days in the W and M classes. Here, RegCM4 has too many days in the W class throughout but does better for the M class. REMO and RCA often underestimate the W-class while overestimating the number of days in the M-class. Some models do better for some stations, for example, RCA largely overestimate the W class for all stations except Shambat, whereas REMO does the same but only at Wad Madeni and Kosti. It is notable that with the exception of showing at least a few days in the S and WS classes, the TRMM does not seem to generally outperform the models as compared

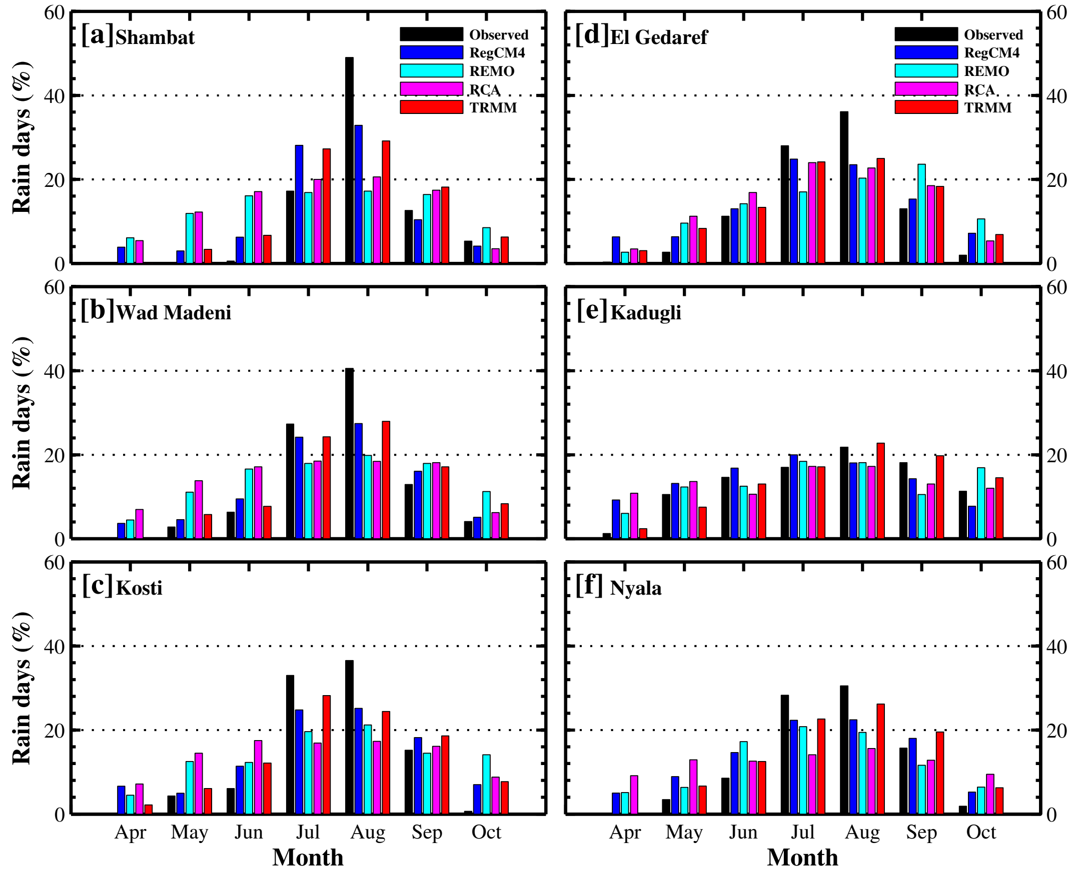

Fig. 6. Median frequency of the rain-days in the month expressed in percentage of the total rain-days.

to the station data for this particular metric.

4.4. Contribution of rain-day classes to total annual rainfall amount

The median contribution of the classes to the total annual rainfall amount is given in Fig. 5. From the station observations, one can see that the VS rainfall class contributes the most to the total annual rainfall, with as much as 28–42% across the stations. Recent studies conclude that the annual rainfall in this region is highly dependent on heavy rainfalls, thus the VS class yields a large contribution to the total annual rainfall in this region (Elagib, 2010b; Sulieman and Elagib, 2012; Mahmoud et al., 2014). In TRMM, the lead contributor is the M class, accounting for 38–40% of the total, whereas the VS class contributes anywhere from 0% in Shambat (Fig. 5a) to 28% in El Gedaref (Fig. 5d).

REMO captures part of the VS class contribution at the extremely arid station Shambat and the two southernmost semi-arid stations Nyala and Kadugli. RCA fails to capture the contribution of this class to the total rain amount, and hence, this model is only able to estimate less than a quarter of the contribution at the northernmost part of the region. These results agree with the previously described lack of rain days in the stronger classes in RCA and REMO. RegCM4 performance in this class varies widely among the stations, between poor results for Shambat to being almost perfect at Kadugli. RCA and REMO grossly overestimate the contribution of the M class across the region. While the observed contribution of this class varies from 17 to 28% across the six stations, the corresponding range in the models is 36–48%, 43–70% and 41–83% for RegCM4, REMO and RCA, respectively. The contribution of the MS class as recorded at the stations varies from 17 to 30%, which is reasonably well captured by REMO and RCA for most of the stations, except Shambat and El Gedaref (Fig. 5a, d). Similar conclusions can be drawn for the S class in REMO and RCA, except at Shambat. RegCM4 closely captures the contribution of the MS class at three stations (Fig. 5c–e), underestimates it for two stations (Fig. 5b and f) and overestimates it significantly at one station (Fig. 5a). Considering the W class, it is the smallest contributor in terms of annual rainfall amount, as demonstrated by both the observed and simulated data, despite the fact that it accounts for 15–22% of the number of rain-days.

4.5. Contribution of months to rain-days and rainfall amount

Figs. 6 and 7 show the same type of statistics as in Figs. 4 and 5, but now distributed over the different months instead of over the different classes. Fig. 6 shows the number of rain-days in each month relative to the total annual rain-days for both observations and models, considering only the seven wet months from April to October, since the rest of the year is essentially rain free. There is a pronounced July–August peak observed at all the stations, except at Kadugli (Fig. 6e) where the rain-days are spread more evenly over the months. Kadugli is the southernmost station in the region, where the rainy season is somewhat longer and less varying, compared to the other stations (see Fig. 3e). In the northernmost part of the region, August is the rainiest month, accounting for between 40 and 50% of the rain-days (Fig. 6a and b).

All the models and TRMM agree with the station observations that the highest frequency of rain-days occurs in July and August. They, however, mostly underestimate the peak of rain-days, especially in August compared to the observations. RegCM4 captures the July rainfall reasonably well for three of the station (Fig. 6b, d and e), but differs substantially for the other three. The deviation from the observations reaches 17% for Shambat (Fig. 6a). In most cases, REMO and RCA overestimate the rain-days at the beginning (April–May) and end (September–October) of the season. These differences are statistically significant at the 95% confidence level across most of the stations. Although some positive and negative deviations from the observations

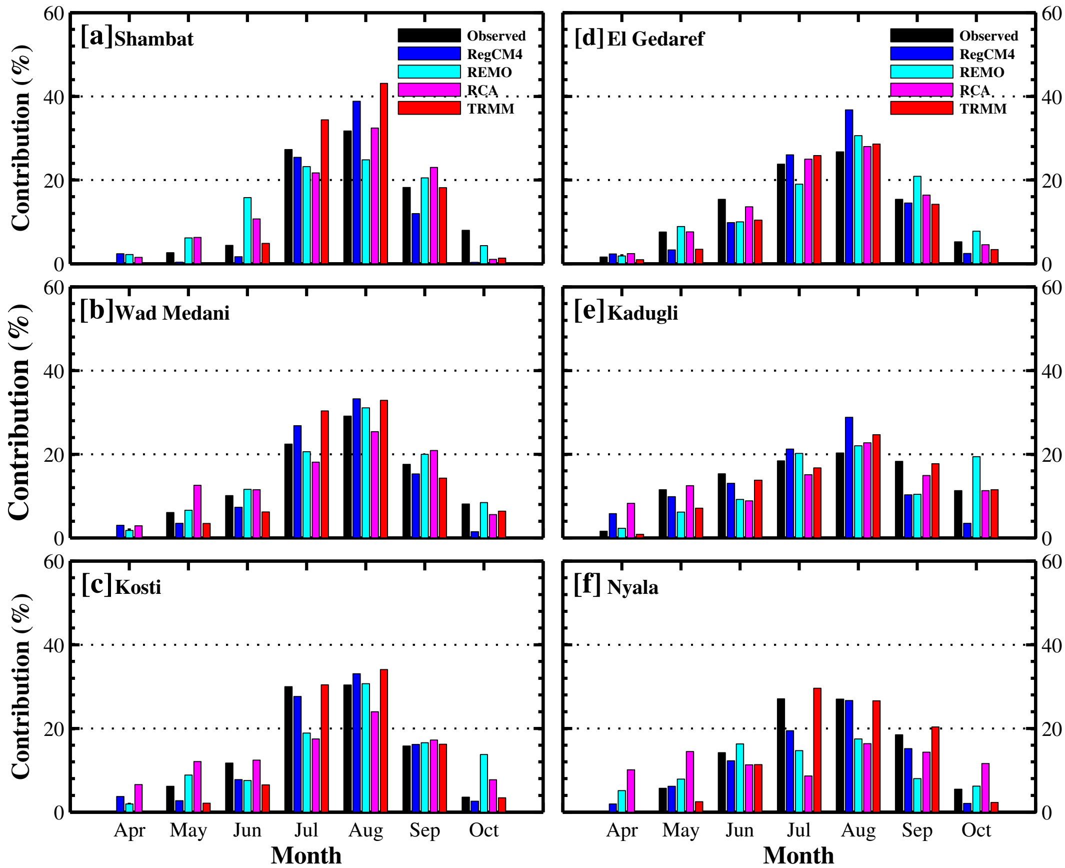

Fig. 7. Median contribution of monthly rainfall amount to the total annual rainfall amount.

occur, the RegCM4 results are somewhat closer to the observations at the beginning (May) and toward the end (September) of the season.

Regarding the contribution of monthly rainfall amounts to the total annual rainfall (Fig. 7), the results in general match those in the previous section. A given month with more rain-days generally yields the larger contribution to the total amount of rainfall. From the observations, the rainfall in July, August and September contribute most to the annual amount by 18–30%, 20–32% and 15–19%, respectively, and TRMM and the station data mostly agree in magnitude. For July, the contribution simulated by RegCM4 stays relatively close to the observed value. In contrast, REMO and RCA underestimate the July contribution at most of the stations. For instance, the July contribution from RCA at Nyala is estimated to be only ~9% while the corresponding value from the observations is ~27% (Fig. 7f). The observed maximum contribution for August is well captured by REMO and RCA; however, RegCM4 overestimates it. In September, REMO underestimates the observed contribution by about 7% at Nyala and overestimates it by about 2% at Shambat. RCA provides a better estimate of the contribution in September, at least at the three arid stations, with no significant differences at 95% confidence level from the observations. REMO also significantly overestimates the contribution of October by 2–10% at three stations (Fig. 7c–e).

5. Discussion

The focus of this study is the analysis of some detailed features of the rainfall in the Sahelian Sudan and to evaluate the performance of three RCMs in terms of their ability to capture these details. Regional and global climate models are fundamental tools for understanding the behavior of the climate system. To fulfill this task, they should exhibit an ability to reproduce the observed climate, not only the averages, but also the whole PDF of the observed climate (Perkins et al., 2007). The analysis carried out in this study has successfully explored the potential of such models for estimating several rainfall variables and the frequency of occurrence of rain-days.

All of the three models under consideration here have been shown to display weaknesses, especially with respect to estimating the strongest rainfall events although these events in reality account for a considerable portion of the total amount of rain annually. Across this region, the rainy season during the boreal summer is generally characterized by convective rainfall, associated with the annual march of the ITCZ (Salih et al., 2013; Nicholson, 2013). Thus, the role of large-scale processes in rainfall, which is a dominant mid-latitude feature (Pal et al., 2007), is expected to be small. Hence, the poor results observed for the strong rain events raise questions regarding the convective parameterizations in these models. We can only speculate on the underlying reasons for these problems. For example, atmospheric convection occurs over many different scales, i.e. from isolated convection at short-time scales over self-organizing convective systems to long-lived convection *organized* by larger-scale motions such as the ITCZ (e.g. Bechtold et al., 2014). Depending on the convection scheme used, different types of convection may be favored and not all convection schemes are optimized and tuned for the type of *organized* convection occurring in the ITCZ. The models also compensate to some degree for the lack of VS rainfall by having more frequent events in the M rainfall class. This is a well-known behavior in almost all atmospheric models (e.g. Ahlgrimm and Forbes, 2014) and is here particularly pronounced in RCA and REMO. This has been shown to occur due to very delicate balances in the process descriptions, but can also be viewed from the context of tuning coarser-scale models against monthly averaged observed rainfall. What the models fail to reproduce as convective precipitation seems to be tuned by generating large-scale precipitation. Moreover, there is a general tendency of the RCMs toward producing more rainfall in the W to M rainfall classes than in the stronger ones;

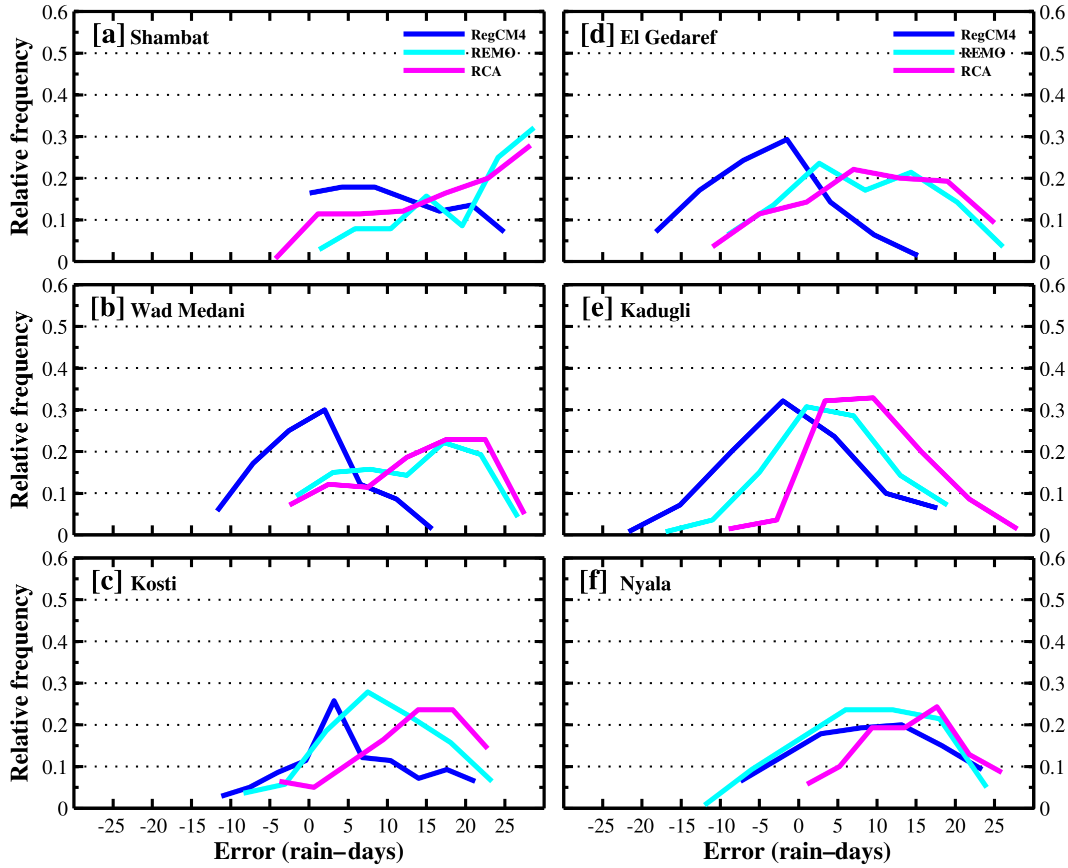

Fig. 8. Probability density function of the error in rain-days computed for April to October. The rest of the year is excluded because it has high likelihood of zero error.

both REMO and RegCM4 simulate more rain-days within the W rainfall class. Ibrahim et al. (2012) drew similar conclusions in an analysis of five RCMs over Burkina Faso in the western part of the Sahel region. They found that "the RCMs generally produce too frequent low rainfall values (between 0.1 and 5 mm/day) and too high extreme rainfalls (more than twice the observed values)".

Pursuing our analysis in this direction, the PDF of error in the monthly number of rain-days and amounts was examined (Figs. 8 and 9). Ideally, the PDF of errors should display a narrow Gaussian shape with a peak at or near zero. Such a shape indicates that the error is small, random and unpredictable. However, the PDFs in Fig. 8 show quite flat and, sometimes, positively-skewed distributions of the errors in the number of rain-days. Moreover, the peak is more often positive than negative. Errors range between − 15 and 30 days, with negative errors representing an underestimation and vice versa. In RegCM4, the error distribution for arid stations, such as Kosti and Wad Medani, and for the semi-arid stations at El Gedaref and Kadugli (Fig. 8b, c, d and e, respectively) indicates relatively random, although sometimes large errors. The performance of RegCM4 for most stations is characterized by a broad error distribution. Such a tendency toward overestimating the number of rain-days per month is consistent with the overestimation of moderate rain-days at the expense of underestimation of very strong rainfall events. Both REMO and RCA show a tendency toward systematic overestimation of the number of rain-days, whereas RegCM4 is only associated with such systematic errors at the northernmost part of the region, i.e. the extremely arid station in Shambat (Fig. 8a).

In terms of the monthly rainfall amount, the peaks of the PDFs are close to zero but vary from station to station with typical errors of ± 200 mm (Fig. 9). The performance of RegCM4 over Wad Medani, Kosti, El Gedaref and Kadugli (Fig. 9b, c, d, and e, respectively) appears reasonably random, but REMO and RCA show a persistent overestimation tail in the PDF. As for the rest of the stations, the errors in RegCM4 show similar behavior, like REMO and RCA displaying a broader distribution.

Although the errors in the monthly amount (Fig. 9) are distributed around zero, with negative and positive values, as if they are randomly distributed, the distributions are very wide and the probability of producing a relatively large error (± 20–50 mm/month) is high at some of the stations. This is likely due to simulation of too early onsets of the rainy season by the models (Fig. 2). All models have rainfall in April, which is generally a dry month at most of the stations. In general, the onset of the rainy season in this region is characterized by erratic and variable behavior, hence leading to discrepancies in the monthly rainfall amount between the models and the observations.

As the convective schemes are expected to be a potential source of model errors (Perkins et al., 2007), we investigated this by separately examining the two components of rainfall, i.e. convective and total. Fig. 10 compares the annual cycle of the observed rainfall with the convective and total rainfalls in RegCM4 and RCA; no separate information for convective rainfall was available from REMO. The difference between the total and convective rainfalls must be due to the large-scale precipitation. RegCM4 shows that convective rainfall dominates, especially at two of the arid stations (Fig. 9a and c), with a slight contribution from the large-scale component only during the wettest months (July and August). For all of these stations, the performance of the model is acceptable although an earlier rainfall peak is noticeable in June. Nevertheless, at the other two semi-arid stations, a large deviation of the model results from the observations is present, with an underestimation at one station (Fig. 10d) and a slight overestimation of the total rainfall at the other one (Fig. 10e). Hence, RegCM4 performs reasonably well in simulating the rainfall in this region of Africa whenever the convective rainfall is correctly simulated. This is because convective precipitation is the main contributor to the total annual

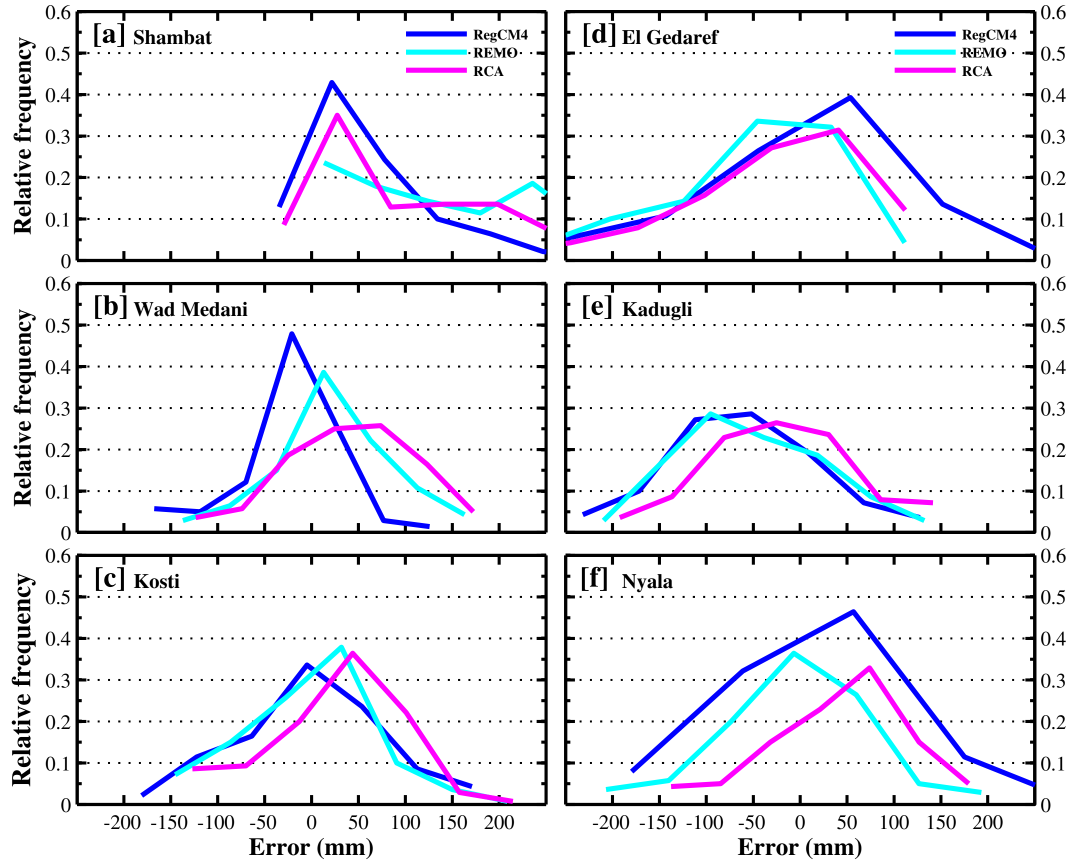

Fig. 9. Probability density function of the error in monthly rain amount computed for April to October. The rest of the year is excluded because it has high likelihood of zero error.

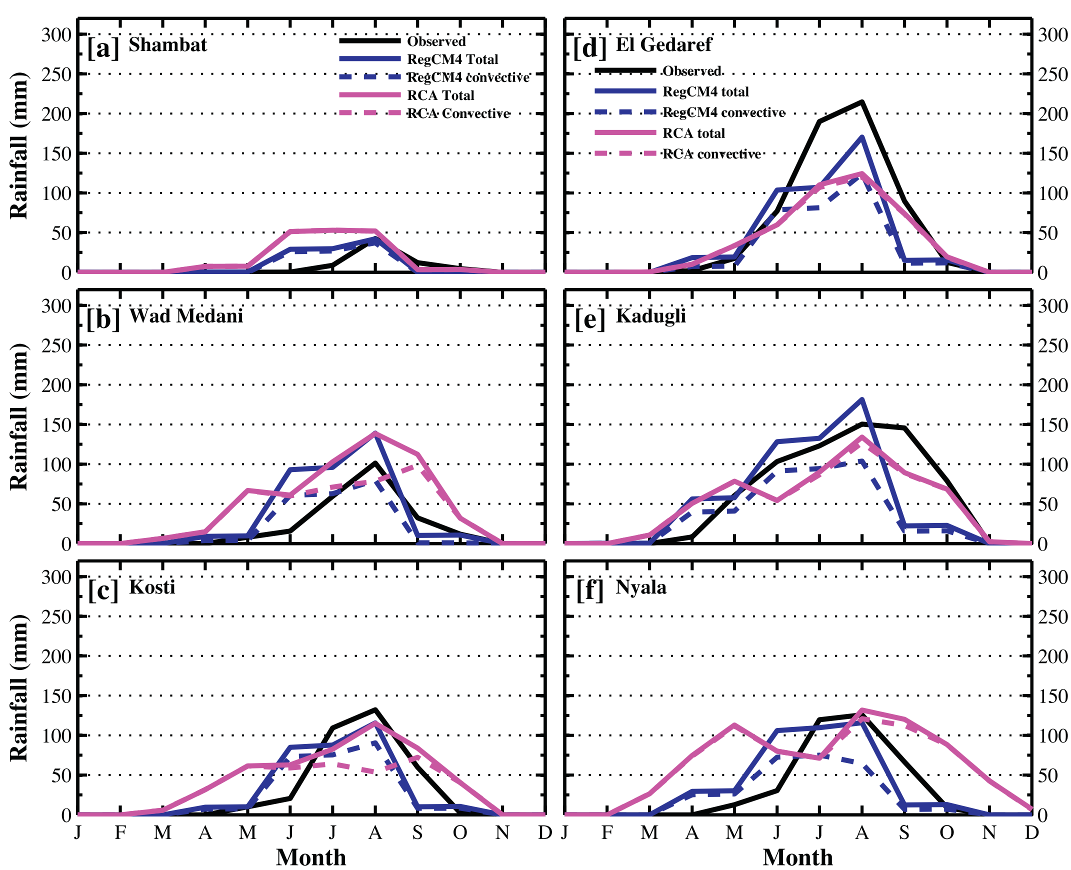

Fig. 10. Annual cycle of total (solid lines) and convective (dashed lines) rainfalls from observations, RegCM4 and RCA.

precipitation. According to Taylor and Lebel (1998), when the Sahelian soil becomes moist, convective activity tends to persist for a longer time.

RCA differs markedly from RegCM4. Across all the semi-arid stations (Fig. 10d, e and f), the total rainfall comes from convection only, whereas in the arid region, except at Shambat (Fig. 10a), large-scale precipitation plays a significant role but only during July–September. The convective rainfall at the three arid stations always remains more or less at 50 to 75 mm/month during May through September. June through September is the heart of the rainy season, and rainfall during these months is expected to be caused mainly by convection. The clearly unrealistic double peaks in May and August/September in the annual cycle of RCA rainfall seems to come mainly from the convection scheme. Although it is unclear why all the rainfall at four of the stations is due to convection alone, several potential factors for the erroneous convective activities in RCMs can play a role. For example, an unrealistic surface energy balance might reduce/increase boundary-layer buoyancy, hence hindering/enhancing convective activity (Yin et al., 2013). Errors in the description of the surface properties and/or in terrain height differences could constitute a further explanation of this behavior.

6. Summary and conclusions

In this study, the rain-days in Sahelian Sudan were grouped into five rainfall-amount classes, using high-quality observational data. The corresponding frequency of occurrences and contribution to both the total annual number of rain-days and the annual amount of rainfall are examined. These observations reveal that most of the daily rainfall across the region is classified as "weak to moderate" rains, which represent 60–75% of the rain events. The moderately strong rain-days account for 10%–18% of the total annual rain-days, whereas the strong rain-days contribute only < 6%. Although the latter type of rain-days (> 30 mm/day) is the least recurrent across the region, it contributes significantly to the total annual rainfall amount, about 28–42%.

The performance of three RCMs in producing the observed details of rainfall in Sahelian Sudan was also evaluated. The three models vary in terms of their formulations and physical parameterizations. One model has an Eulerian advection core while two have semi-Lagrangian advection schemes, and they also differ in the formulation of the model physics, i.e. convection, radiation, boundary layer, cloud microphysics etc. Our evaluation covers a wide span of timescales, i.e. from daily through monthly to annual scales of the simulated rainfall.

The ability of the models to simulate the observed spatial distribution of the rainfall and its annual cycle at six stations spread over Sahelian arid and semi-arid environments were examined. RegCM4 was shown to yield an annual rainfall cycle in close agreement with the observations at four stations, but its results deviate from stations data for two semi-arid stations. RCA featured a strange double peak, with one early unrealistic secondary maximum in May and the main maximum in August; this is the rainiest month. REMO clearly underestimates the rainfall at five stations while RCA overestimates it at the most arid location. Regarding the spatial distribution, both RegCM4 and RCA have better simulated the observed pattern than ERA-interim does. Compared to CRU, both REMO and TRMM slightly underestimated the rainfall amount over Sahelian Sudan.

All the three models failed to capture the observed rain-day frequency of the stronger rain classes, with RegCM4 being the closest to the observations for the MS rain-day class at one station only. RegMC4 was also the closest to the stations in reproducing the occurrences of moderate rain-days at five stations. The results from REMO are partly closer to the observation over the semi-arid locations. The behavior of this model regarding the contribution of the classes to the total rainfall amount involves large errors, showing both over- and under-estimations. However, the underestimation of both the number of rain-days and rainfall amount in the VS class by REMO is outweighed by overestimating the rainfall in the M class. Other studies, for the western African Sahel (e.g. Ibrahim et al., 2012), have also shown the tendency of RCMs toward overestimating the weak to moderate rainfall, but in contrast to our results, there was also a tendency to overestimate the VS rainfall.

For all the stations, the PDF of error in the number of rain-days, especially in REMO and RCA, is positively skewed. The PDF of the error for RegCM4 over two arid stations, however, tends to take the shape of a normal distribution. The spread of error distribution in the monthly rainfall amounts is large (± 200 mm), most likely due to inter-annual variability, especially during the onset of the rainy season. The modeled rainy season starts earlier and ends later in comparison to the observations at most of the stations. In RegCM4, most of the rainfall over this region occurs as convective rainfall. RCA produces relatively small amounts of convective rainfall, which also starts too early, i.e. in April. This is likely responsible for the unexpected double-peak behavior. Later, during the main wet season (June to September), rainfall induced by large-scale activities starts to become a significant part of the total rainfall. For the two climate regimes (arid and semi-arid), the performance of RegCM4 is somewhat similar to the observations, however, with positive and negative deviations from the observed climate. REMO consistently underestimates the annual cycle whereas RCA shows varying behavior over the region.

The results from this study can serve two different communities. First, concerning the development of climate models, the findings underscore an urgent need for careful model improvements in order to overcome, or at least reduce, the uncertainty in the emerging results to match the observed regional climate. Climate is a strongly coupled system, and any errors related to cloud representation can result in unrealistic representation of rainfall. The latter might influence the energy budget of the models and, hence, other variables such as surface temperature. Second, the output from RCMs has a wide range of modeling applications in many fields, such as hydrology, agriculture, water-resource management, wind energy, etc. The present study provides an insight into the limitations of RCMs. Hence, the users of such products should be aware of these limitations. Modeling issues, such as unsatisfactory reproduction of the observed climate variability in the Sahel zone, imply uncertainties in future climate projections for this region. They have largely hindered the quantification of future vulnerability of this area and the associated problems affecting the decision-making process (Challinor et al., 2007; Dessai et al., 2009; Conway and Schipper, 2011; Ben Mohamed, 2011).

Acknowledgments

We thank Grigory Nikulin and Patrick Samuelsson from the Swedish Hydrological and Meteorology Institute, Andreas Hänsler from the Climate Services Center, and Alberto Elizalde from Max Planck Institute for Meteorology for providing the model data. The second author would like to thank the International Meteorological Institute at Stockholm University for hosting his visit during which this work was initiated. He also wishes to thank the Alexander von Humboldt Foundation, Germany, for supporting the research stay at ITT, Technische Hochschule Köln, which led to this research collaboration. Our thanks also extend to the Swedish National Infrastructure for Computing (SNIC) and the National Supercomputing Center (NSC) for providing the computing resources for the RegCM4 simulation.

References

Abtew, W., Melesse, A.M., Dessalegne, T., 2009. Spatial, inter and intra-annual variability of the Upper Blue Nile Basin rainfall. Hydrol. Process. 23, 3075–3082.

Ahlgrimm, M., Forbes, R., 2014. Improving the representation of low clouds and drizzle in the ECMWF model based on ARM observations from the Azores. Mon. Wea. Rev. 142, 668–685. http://dx.doi.org/10.1175/MWR-D-13-00153.1.

Balogun, O.L., 2011. Sustainable agriculture and food crisis in sub-Sahara Africa. Chapter 20. In: Behnassi, M., Draggan, S., Yaya, S. (Eds.), Global Food Insecurity: Rethinking

Agricultural and Rural Development Paradigm and Policy, pp. 283–297.
Batterbury, S., Warren, A., 2001. The African Sahel 25 years after the great drought: assessing progress and moving towards new agendas and approaches. Glob. Environ. Chang. 11, 1–8.
Bechtold, P., Semane, N., Lopez, P., Chaboureau, J., Beljaars, A., Bormann, N., 2014. Representing equilibrium and nonequilibrium convection in large-scale model. J. Atmos. Sci. 71, 734–753. http://dx.doi.org/10.1175/JAS-D-13-0163.1.
Ben Mohamed, A., 2011. Climate change risks in Sahelian Africa. Reg. Environ. Chang. 11 (Suppl. 1), S109–S117.
Brunet, M., Jones, P., 2011. Data rescue initiatives: bringing historical climate data into the 21st century. Clim. Res. 47, 29–40.
Challinor, A., Wheeler, T., Garforth, C., Craufurd, P., Kassam, A., 2007. Assessing the vulnerability of food crop systems in Africa to climate change. Clim. Chang. 83, 381–399.
Christensen, J.H., Machenhauer, B., Jones, R.G., Schar, C., Ruti, P.M., Castro, M., Visconti, G., 1997. Validation of present-day regional climate simulations over Europe: LAM simulations with observed boundary conditions. Clim. Dyn. 13, 489–506. http://dx.doi.org/10.1007/s003820050178.
Conway, D., Schipper, E.L.F., 2011. Adaptation to climate change in Africa: challenges and opportunities identified from Ethiopia. Glob. Environ. Chang. 21, 227–237.
Dai, A., Lamb, P.J., Trenberth, K.E., Hulme, M., Jones, P.D., Xie, P., 2004. The recent Sahel drought is real. Int. J. Climatol. 24, 1323–1331.
Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M.A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A.C.M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A.J., Haimberger, L., Healy, S.B., Hersbach, H., Hólm, E.V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A.P., Monge-Sanz, B.M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., Vitart, F., 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Q. J. R. Meteorol. Soc. 137, 553–597. http://dx.doi.org/10.1002/qj.828.
Dessai, S., Hulme, M., Lempert, R., Pielke, R., 2009. Climate prediction: a limit to adaptation. In: Adger, N., Lorenzoni, I., O'Brien, K. (Eds.), Adapting to Climate Change: Thresholds, Values, Governance. Cambridge University Press, Cambridge, UK.
Diatta, S., Fink, A.H., 2014. Statistical relationship between remote climate indices and West African monsoon variability. Int. J. Climatol. 34 (12), 3348–3367.
Dickinson, R.E., Henderson, S.A., Kennedy, P.J., 1993. Biosphere–atmosphere Transfer Scheme (BATS) Version 1E as Coupled to the NCAR Community Climate Model. Technical Note NCRA/TN 387 + STR. pp. 72.
El Tahir, M.E., Kääb, A., Xu, C.Y., 2010. Identification and mapping of soil erosion areas in the Blue Nile, Eastern Sudan using multispectral ASTER and MODIS satellite data and the SRTM elevation model. Hydrol. Earth Syst. Sci. 14, 1167–1178.
Elagib, N.A., 2010a. Trends in intra-and inter-annual temperature variabilities across Sudan. Ambio 39 (5–6), 413–429.
Elagib, N.A., 2010b. Exploratory analysis of rain days in central Sudan. Meteorog. Atmos. Phys. 109 (1–2), 47–59.
Elagib, N.A., 2011. Changing rainfall, seasonality and erosivity in the hyper-arid zone of Sudan. Land Degrad. Dev. 22 (6), 505–512.
Elagib, N.A., 2014. Development and application of a drought risk index for food crop yield in Eastern Sahel. Ecol. Indic. 43, 114–125.
Elagib, N.A., Elhag, M.M., 2011. Major climate indicators of ongoing drought in Sudan. J. Hyrol. 409, 612–625.
Eldredge, E., Khalil, S.E., Nicholds, N., Abdalla, A.A., Rydjeski, D., 1988. Changing rainfall patterns in western Sudan. Int. J. Climatol. 8, 45–53.
Eltahir, E.A.B., 1992. Drought frequency analysis of annual rainfall series in central and western Sudan. Hydrol. Sci. J. 37 (3), 185–199.
Feser, F., Rockel, B., Von Storch, H., Winterfeldt, J., Zahn, M., 2011. Regional climate models add value to global model data: a review and selected examples. Bull. Am. Meteorol. Soc. 92 (9), 1181–1192.
Fontaine, B., Roucou, P., Gaetani, M., Marteau, R., 2011. Recent changes in precipitation, ITCZ convection and northern tropical circulation over North Africa (1979–2007) Int. J. Climatol. 31, 633–648. http://dx.doi.org/10.1002/joc.2108.
Fritsch, J.M., Chappell, C.F., 1980. Numerical prediction of convectively driven mesoscale pressure systems. Part I: convective parameterization. J. Atmos. Sci. 37, 1722–1733.
Giorgetta, M., Wild, M., 1995. The water vapour continuum and its representation in ECHAM4. MPI Rep. 162, 38.
Giorgi, F., Coppola, E., Solmon, F., Mariotti, L., et al., 2012. RegCM4: model description and preliminary tests over multiple CORDEX domains. Clim. Res. 52, 7–29. http://dx.doi.org/10.3354/cr01018.
Grell, G.A., Dudhia, J., Stauffer, D.R., 1994. Description of the Generation Penn State/NCAR Mesoscale Model (MM5). Technical Note No. TN-398 + STR. National Center for Atmospheric Research, Boulder, pp. 121.
Hagemann, S., 2002. An improved land surface parameter dataset for global and regional climate models. MPI Rep. 336, 21.
Harris, I.P.D.J., Jones, P.D., Osborn, T.J., Lister, D.H., 2014. Updated high-resolution grids of monthly climatic observations–the CRU TS3. 10 dataset. Int. J. Climatol. 34 (3), 623–642. http://dx.doi.org/10.1002/joc.3711.
Hudson, D.A., Jones, R.G., 2002. Regional Climate Model Simulations of Present-day and Future Climates of Southern Africa, Hadley Centre Tech. Note 39, August.
Huffman, G.J., Adler, R.F., Arkin, P., Chang, A., Ferraro, F., Gruber, A., Janowiak, J., McNab, A., Rudolf, B., Schneider, U., 1997. The global precipitation climatology project (GPCP) combined precipitation dataset. Bull. Am. Meteorol. Soc. 78, 5–20.
Huffman, G.J., Adler, R.F., Bolvin, D.T., Gu, G., Nelkin, E.J., Bowman, K.P., Hong, Y., Stocker, E.F., Wolff, D.B., 2007. The TRMM multi-satellite precipitation analysis: quasi-global, multi-year, combined-sensor precipitation estimates at fine scale. J. Hydrometeorol. 8, 38–55. http://dx.doi.org/10.1175/JHM560.1.
Hui, W.J., Cook, B.I., Ravi, S., Fuentes, J.D., D'Odorico, P., 2008. Dust rainfall feedbacks in the West African Sahel. Water Resour. Res. 44, W05202. http://dx.doi.org/10.1029/2008WR006885.
Hulme, M., 1990. The changing rainfall resources of Sudan. Trans. Inst. Br. Geogr. 15, 21–34.
Ibrahim, B., Polcher, J., Karambiri, H., Rockel, B., 2012. Characterization of the rainy season in Burkina Faso and it's representation by regional climate models. Clim. Dyn. 39, 1287–1302. http://dx.doi.org/10.1007/s00382-011-1276-x.
IPCC, Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., 2007a. Randall, D.A., Wood, R.A., Bony, S., Colman, R., Fichefet, T., Fyfe, J., Kattsov, V., Pitman, A., Shukla, J., Srinivasan, J., Stouffer, R.J., Sumi, A., Taylor, K.E., 2007. Climate models and their evaluation. In: Tignor, M., Miller, H.L. (Eds.), Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
IPCC, 2007b. In: Pachauri, R.K., Reisinger, A. (Eds.), Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Core Writing Team. IPCC, Geneva, Switzerland, pp. 104.
Jacob, D., 2001. A note to the simulation of the annual and inter-annual variability of the water budget over the Baltic Sea drainage basin. Meteorog. Atmos. Phys. 77, 61–73.
Jones, C., Giorgi, F., Asrar, G., 2011. The Coordinated Regional Downscaling Experiment: CORDEX, an international downscaling link to CMIP5: CLIVAR exchanges, no. 56, vol 16, no. 2 pp. 34–40. Retrieved from: http://www.clivar.org/sites/default/files/imported/publications/exchanges/Exchanges_56.pdf.
Kain, J.S., Fritsch, J.M., 1990. A one-dimensional entraining/detraining plume model and its application in convective parameterization. J. Atmos. Sci. 47, 2784–2802.
Kain, J.S., Fritsch, J.M., 1993. Convective parameterization for mesoscale models: the Kain-Fritsch scheme. The representation of cumulus convection in numerical models. Meteor. Monogr., No. 24. Amer. Meteor. Soc. 165–170.
Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Leetmaa, A., Reynolds, R., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J., Mo, K.C., Ropelewski, C., Wang, J., Jenne, R., Joseph, D., 1996. The NCEP/NCAR 40-year reanalysis project. Bull. Am. Meteorol. Soc. 77, 437–471. http://dx.doi.org/10.1175/1520-0477(1996)077 < 0437:TNYRP > 2.0.CO;2.
Kendon, E.J., Roberts, N.M., Senior, C.A., Roberts, M.J., 2012. Realism of rainfall in a very high-resolution regional climate model. J. Clim. 25, 5791–5806. http://dx.doi.org/10.1175/JCLI-D-11-00562.1.
Kiehl, J.T., Hack, J.J., Bonan, G.B., Boville, B.A., Briegleb, B.P., Williamson, D.L., Rasch, P.J., 1996. Description of the NCAR Community Climate Model (CCM3), Technical Report No. TN-420 + STR. National Center for Atmospheric Research, Boulder, pp. 152.
Kistler, R., Collins, W., Saha, S., White, G., Woollen, J., Kalnay, E., Chelliah, M., Ebisuzaki, W., Kanamitsu, M., Kousky, V., van den Dool, H., Jenne, R., Fiorino, M., 2001. The NCEP–NCAR 50–year reanalysis: monthly means CD–ROM and documentation. Bull. Am. Meteorol. Soc. 82, 247–267. http://dx.doi.org/10.1175/1520-0477(2001)082 < 0247:TNNYRM > 2.3.CO;2.
Lebel, T., Ali, A., 2009. Recent trends in the Central and Western Sahel rainfall regime (1990–2007). J. Hydrol. 375 (1), 52–64.
L'Hote, Y., Mahe, G., Some, B., Triboulet, J.P., 2002. Analysis of a Sahelian index from 1896 to 2000; the drought continues. Hydrol. Sci. J. 47 (4), 563–572.
Liang, X.Z., Pan, J., Zhu, J., Kunkel, K.E., Wang, J.X.L., Dai, A., 2006. Regional climate model downscaling of the U.S. summer climate and future change. J. Geophys. Res. 111, D10108.
Liu, W., Wei, X., Fan, H., Guo, X., Liu, Y., Zhang, M., Li, Q., 2015. Response of flow regimes to deforestation and reforestation in a rain-dominated large watershed of subtropical China. Hydrol. Process. 29, 5003–5015. http://dx.doi.org/10.1002/hyp.10459.
Mahmoud, W.H., Elagib, N.A., Gaese, H., Heinrich, J., 2014. Rainfall conditions and rainwater harvesting potential in the urban area of Khartoum. Resour. Conserv. Recycl. 91, 89–99.
Morcrette, J.J., Smith, L., Fouquart, Y., 1986. Pressure and temperature dependence of the absorption in longwave radiation parametrizations. Beitr. Phys. Atmos. 59, 455–469.
Moufouma-Okia, W., Rowell, D.P., 2010. Impact of soil moisture initialization and lateral boundary conditions on regional climate model simulations of the West African Monsoon. Clim. Dyn. 35, 213–229. http://dx.doi.org/10.1007/s00382-009-0638-0.
New, M., Hulme, M., Jones, P., 2000. Representing twentieth-century space-time climate variability. Part II: development of 190196 monthly grids of terrestrial surface climate. J. Clim. 10, 2217–2238.
Nicholson, S.E., 2005. On the question of the “recovery” of the rains in the West African Sahel. J. Arid Environ. 63, 615–641.
Nicholson, S.E., 2013. The West African Sahel: a review of recent studies on the rainfall regime and its interannual variability. ISRN Meteorol. 2013, 453521. http://dx.doi.org/10.1155/2013/453521. (32, 2013).
Nikulin, G., Jones, C., Giorgi, F., Asrar, G., Büchner, M., Cerezo-Mota, R., Christensen, O.B., Déqué, M., Fernandez, J., Hänsler, A., van Meijgaard, E., Samuelsson, P., Sylla, M.B., Sushama, L., 2012. Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. J. Clim. 25, 6057–6078. http://dx.doi.org/10.1175/JCLI-D-11-00375.1.
Pal, J.S., Giorgi, F., Bi, X., Elguindi, N., Solomon, F., Gao, X., Francisco, R., Zakey, A., Winter, J., Ashfaq, M., Syed, F., Bell, J.L., Di_anbaugh, N.S., Kamacharya, J., Konare, A., Martinez, D., da Rocha, R.P., Sloan, L.C., Steiner, A., 2007. The ICTP RegCM3 and RegCNET: regional climate modeling for the developing world. Bull. Am. Meteorol.

Soc. 88, 1395–1409.
Perkins, S.E., Pitman, A.J., Holbrook, N.J., McAneney, J., 2007. Evaluation of the AR4 climate models' simulated daily maximum temperature, minimum temperature, and precipitation over Australia using probability density functions. J. Clim. 20, 4356–4376. http://dx.doi.org/10.1175/JCLI4253.1.
Pfeifroth, U., Trentmann, J., Fink, A.H., Ahrens, B., 2016. Evaluating satellite-based diurnal cycles of precipitation in the African tropics. J. Appl. Meteorol. Climatol. 55 (1), 23–39.
Rechid, D., Raddatz, T.J., Jacob, D., 2009. Parameterization of snow-free land surface albedo as a function of vegetation phenology based on MODIS data and applied in climate modelling. Theor. Appl. Climatol. 95, 245–255.
Rivington, M., Matthews, K.B., Bellocchi, G., 2006. Evaluating uncertainty introduced to process-based simulation model estimates by alternative sources of meteorological data. Agric. Syst. 88, 451–471.
Rummukainen, M., 2010. State-of-art with regional climate models. WIREs Clim. Change 1, 82–96. http://dx.doi.org/10.1002/wcc.8.
Salih, A.A.M., Körnich, H., Tjernström, M., 2013. Climate consequences of deforestations over South Sudan in a regional climate model. Int. J. Climatol. 33 (10), 2362–2375. http://dx.doi.org/10.1002/joc.3586.
Samuelsson, P., Gollvik, S., Ullerstig, A., 2006. The land-surface scheme of the Rossby Centre Regional Atmospheric Climate Model (RCA3). Swedish Meteorological and Hydrological Institute Meteorology Rep. 122. (25 pp).
Samuelsson, P., Jones, C.G., Willén, U., Ullerstig, A., Gollvik, S., Hansson, U.L.F., Jansson, C., Kjellström, E., Nikulin, G., Wyser, K., 2011. The Rossby Centre Regional Climate model RCA3: model description and performance. Tellus A 63 (1), 4–23.
Sanogo, S., Fink, A.H., Omotosho, J.A., Ba, A., Redl, R., Ermert, V., 2015. Spatio-temporal characteristics of the recent rainfall recovery in West Africa. Int. J. Climatol. 35 (15), 4589–4605.
Sass, B.H., Rontu, L., Savijärvi, H., Räisänen, P., 1994. HIRLAM-2 Radiation Scheme: Documentation and Tests. SMHI HIRLAM Tech. Rep. 16. pp. 43.
Savijärvi, H., 1990. A fast radiation scheme for mesoscale model and short-range forecast models. J. Appl. Meteorol. 29, 437–447.
Schoetter, R., Hoffmann, P., Rechid, D., Schlünzen, K.H., 2012. Evaluation and bias correction of regional climate model results using model evaluation measures. J. Appl. Meteorol. Climatol. 51, 1670–1684.
Schoof, J.T., Pryor, S.C., 2003. Evaluation of the NCEP–NCAR reanalysis in terms of synoptic-scale phenomena: a case study from the Midwestern USA. Int. J. Climatol. 23, 1725–1741. http://dx.doi.org/10.1002/joc.969.
Segele, Z.T., Leslieb, L.M., Lamb, P.J., 2009. Evaluation and adaptation of a regional climate model for the Horn of Africa: rainfall climatology and interannual variability. Int. J. Climatol. 29, 47–65.
Seleshi, Y., Zanke, U., 2004. Recent changes in rainfall and rainy days in Ethiopia. Int. J. Climatol. 24 (8), 973–983.
Small, E.E., Giorgi, F., Sloan, L.C., 1999. Regional climate model simulation of precipitation in central Asia: mean and interannual variability. J. Geophys. Res. 104D, 6563–6582.
Sulieman, H.M., Elagib, N.A., 2012. Implications of climate, land-use and land-cover changes for pastoralism in Eastern Sudan. J. Arid Environ. 85, 132–141.
Sylla, M.B., Coppola, E., Mariotti, L., Giorgi, F., Ruti, P.M., Dell'Aquila, A., Bi, X., 2010. Multiyear simulation of the African climate using a regional climate model (RegCM3) with the high resolution ERA-interim reanalysis. Clim. Dyn. 35 (1), 231–247.
Szczypta, C., Calve, J.C., Albergel, C., Balsamo, G., Boussetta, S., Carrer, D., Lafont, S., Meurey, C., 2011. Verification of the new ECMWF ERA-interim reanalysis over France. Hydrol. Earth Syst. Sci. 15, 647–666. http://dx.doi.org/10.5194/hess-15-647-2011.
Taddese, G., 2001. Land degradation: a challenge to Ethiopia. J. Environ. Manag. 27 (6), 815–824.
Tang, H., Micheels, A., Eronen, J., Fortelius, M., 2011. Regional climate model experiments to investigate the Asian monsoon in the Late Miocene. Clim. Past 7, 847–868. http://dx.doi.org/10.5194/cp-7-847.
Taylor, K.E., 2001. Summarizing multiple aspects of model performance in a single diagram. J. Geophys. Res. 106, 7183–7192.
Taylor, C.M., Lebel, T., 1998. Observational evidence of persistent convective-scale rainfall patterns. Mon. Weather Rev. 126, 1597–1607. http://dx.doi.org/10.1175/1520-0493(1998)126<1597:OEOPCS>2.0.CO;2.
Tiedtke, M., 1989. A comprehensive mass flux scheme for cumulus parameterization in largescale models. Mon. Weather Rev. 117, 1779–1800.
Tilahun, K., 2006. The characterisation of rainfall in the arid and semi-arid regions of Ethiopia. Water SA 32.
Washington, R., Kay, G., Harrison, M., Conway, D., Black, E., Challinor, A., Grimes, D., Jones, R., Morse, A., Kay, G., Todd, M., 2006. African climate change: taking the shorter route. Bull. Am. Meteorol. Soc. 87 (10), 1355–1366.
Wickens, G.E., 1997. Has the Sahel a future? J. Arid Environ. 37, 649–663.
Yin, L., Fu, R., Shevliakova, E., Dickinson, R.E., 2013. How well can CMIP5 simulate precipitation and its controlling processes over tropical South America? Clim. Dyn. 41 (11–12), 3127–3143. http://dx.doi.org/10.1007/s00382-012-1582-y.
Zhang, Q., Körnich, H., Holmgren, K., 2013. How well do reanalyses represent the southern African precipitation? Clim. Dyn. 40, 951–962. http://dx.doi.org/10.1007/s00382-012-1423-z.