



Research papers

Analyses of rainfall trends in the Nile River Basin

Charles Onyutha^{a,b,*}, Hossein Tabari^a, Meron T. Taye^c, Gilbert N. Nyandwaro^a, Patrick Willems^a^a Department of Civil Engineering, KU Leuven, Kasteelpark Arenberg 40, Leuven B-3001, Belgium^b Faculty of Technoscience, Muni University, P.O. Box 725, Arua, Uganda^c University of Wisconsin, Madison Room 1261A, Engineering Hall, 1415 Engineering Drive, Madison, WI 53706, USA

Received 31 December 2014; revised 21 September 2015; accepted 29 September 2015

Abstract

Trends in rainfall at 39 locations of the Nile River Basin (NRB) in Africa were analyzed. Comparison was made between rainfall trend results from the long-term data and those of short-term series selected over different time periods. The bias on trend results from series of short-term records was quantified. Homogeneity test was conducted to assess the coherence of the trend directions on a regional basis. Based on an assumed population (for simplicity) of rainfall data time periods in the range 75–100 years, bias in the short-term trend analysis was noted to reduce by about 10% for every 10% increase in record length. Under some conditions if respected, it was possible to derive trends at stations with short records based on those at nearby stations with longer term records but in the same region. Using the same data record length and uniform time period at all the selected stations, an improved regional coherence of rainfall trend results was obtained. In the equatorial region, trend in annual rainfall was found mainly positive and significant at level $\alpha = 5\%$ in 4 of the 7 stations. Collectively for Sudan, Ethiopia and Egypt, trends in the annual rainfall were mostly negative and significant at $\alpha = 5\%$ in 69% of the 32 stations. Heterogeneity in the trend directions for the entire NRB was confirmed at $\alpha = 1\%$ in 13% of the 39 stations. These findings are vital for water and agricultural management practices.

© 2015 International Association for Hydro-environment Engineering and Research, Asia Pacific Division. Published by Elsevier B.V. All rights reserved.

Keywords: Trend analysis; Trend homogeneity; Sub-trend identification; Mann–Kendall test; Rainfall; Nile River Basin

1. Introduction

The warming and changes in all components of the climate system can be hypothetically ascribed to the continued increase in greenhouse gas emissions (Intergovernmental Panel on Climate Change, IPCC, 2013). Changes in rainfall can be used to assess the influence of the climate system on hydrology. Some studies conducted recently to determine changes in hydrological variables include Mphale et al. (2014), Onyutha (2015a, 2015b), Shiau and Huang (2015), Stojković et al. (2014), and Syafrina et al. (2014). To detect trends, nonparametric tests are more often used than the parametric ones due to their suitability for data with specific distribution properties (e.g. non Gaussian). Nonparametric trend detection can be carried out using the Spearman's rho (SMR) (Lehmann, 1975; Sneyers, 1990; Spearman, 1904), the Mann–Kendall (MK) (Kendall, 1975; Mann, 1945), and the Cumulative Rank Difference (CRD) (Onyutha, 2015a) test. Close agreement with respect to the

performance of these methods was found between MK and SMR (Yue et al., 2002a) and MK and CRD (Onyutha, 2015a). Thus, the MK test was deemed to be representative and thus adopted for this study. To eliminate autocorrelation which influence trend analysis, von Storch (1995) suggested a pre-whitening. Because the von Storch's approach eliminates a portion of the trend if present, Yue et al. (2002a) proposed a Trend-Free Pre-Whitening (TFPW) for the case when both trend and lag-1 autoregressive process AR(1) exist in a time series.

Some important factors to be considered in trend analysis include data quality, data record length and selected time periods, etc (World Meteorological Organization, WMO, 2000). Although the trend from the full time series may be insignificant, separate analyses done over short time periods may reveal significant sub-trends which are vital to ascertain the influence of short-duration climate fluctuations (Onyutha, 2015a). The influence of short-term data on trend analysis may exist in the form of bias in the trend results. To partly solve this problem of trend bias due to short-term data at a given station, long-term rainfall series from another nearby station can be used. This solution can be adequately implemented if the region in which the stations are selected are homogeneous.

* Corresponding author. Hydraulics Laboratory, KU Leuven, Kasteelpark Arenberg 40, B-3001 Heverlee, Belgium. Tel.: +32 16 32 20 07.

E-mail address: charles.onyutha@bwk.kuleuven.be (C. Onyutha).

In this study area, a number of previous change analyses based on short-term annual rainfall from few meteorological stations have been mostly limited to sub-basins. Moreover, the form of changes analyzed in the rainfall of the study area seem to have mostly been rather decadal or multi-decadal variability than long-term trend; see among others Onyutha (2015b), Onyutha and Willems (2015a, 2015b), and Taye and Willems (2012). Both trend and variability have also occasionally been analyzed, for instance, by Nyeko-Ogiramo et al. (2013). The study by Taye and Willems (2012) on temporal variability of hydro-climatic extremes using the Quantile Perturbation Method (QPM) was limited to the upper Blue Nile basin. Onyutha and Willems (2015b) used the QPM to compute variability in the annual maxima rainfall at some few locations in the Lake Victoria basin. Based on observed hydro-meteorological extremes, the study by Nyeko-Ogiramo et al. (2013) which was also limited to the Lake Victoria basin analyzed trend and variability using the MK test and QPM respectively. In the study by Onyutha and Willems (2015a), station-based data were used to analyze spatiotemporal variability of seasonal and annual rainfall totals using the QPM. The limitations of the studies by Nyeko-Ogiramo et al. (2013), Onyutha and Willems (2015a, 2015b), and Taye and Willems (2012) were that they: (1) did not cover sufficient locations of all the riparian countries of the Nile River Basin (NRB), (2) analyzed variability using the QPM which considers rainfall intensity directly (without rescaling), thereby rendering the method susceptible to possible anomaly exaggeration in case an outlier

exists, (3) did not quantify the uncertainty due to short-data record lengths on the trend or variability results. To take into consideration (1)–(2), using country-wide gridded (instead of station-based) monthly rainfall data, Onyutha (2015b) analyzed variability in all the riparian countries of the NRB using the Nonparametric Anomaly Indicator Method (NAIM). The difference between the QPM and NAIM is that the QPM analyzes variability in terms of the frequency of extreme events and perturbation of rainfall extremes, while the NAIM computes anomalies in the series after applying temporal convolution to the nonparametrically rescaled data set.

Therefore, to differ from other previous studies such as Nyeko-Ogiramo et al. (2013), Onyutha (2015b), Onyutha and Willems (2015a, 2015b), and Taye and Willems (2012) by focusing on trend analyses while investigating the possible bias due to short-term data record lengths, this study was aimed at: (1) determining how data record length and selected time period influence trend results, (2) assessing the bias in trend results due to short-term data length, (3) investigating the homogeneity of the rainfall trend directions, and (4) determining rainfall trends at 39 locations across the entire NRB.

2. Study area and rainfall data

The NRB, which stretches over 35° of latitude in north–south direction (31°N to 4°S) and over 16° of longitude in west–east direction (24 to 40°E), has a total catchment area of about 3 400 000 km² (see Fig. 1). The River Nile which has 11

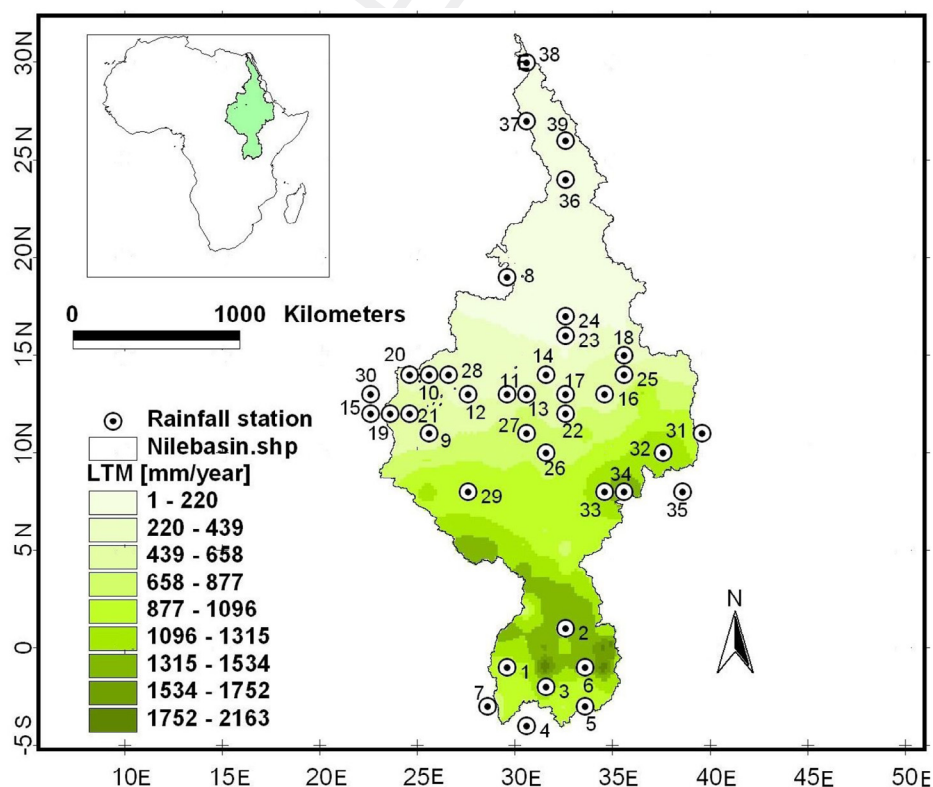


Fig. 1. Locations of the selected meteorological stations (see Table 1 for details) in the Nile basin; the background was obtained by surface interpolation (kriging method) of the Long Term Mean (LTM) of annual rainfall.

Table 1
Overview of the selected meteorological stations and their annual rainfall properties.

SNo.	Rainfall station		Country	Location		Number of years	Annual rainfall [mm]				
	FAO ID	Name		Long.	Lat.		C_v	C_s	K_u	LTM	MAX
1	UG19KBL0	Kabale	Uganda	29.98	-1.25	77	0.17	0.49	0.07	1003	1486
2	UG12NMSG	Namasagali	Uganda	32.93	1.00	64	0.19	1.89	6.12	1256	2345
3	TZ11GBR0	Igabiro	Tanzania	31.53	-1.78	52	0.24	0.82	0.80	1198	2012
4	TZ30KBND	Kibondo	Tanzania	30.68	-3.57	53	0.29	2.47	9.50	1196	2883
5	TZ33SHNW	Shanwa	Tanzania	33.75	-3.15	55	0.24	0.68	0.28	829	1344
6	TZ14TRM0	Tarime	Tanzania	34.37	-1.35	43	0.20	1.48	1.94	1475	2322
7	BI39BJMB	Bujumbura	Burundi	29.32	-3.32	75	0.18	0.27	0.09	251	370
8	SD90DNGL	Dongola	Sudan	30.48	19.17	51	1.30	1.58	1.90	17	84
9	SD16LDN0	El-Da-Ein	Sudan	26.10	11.38	48	0.27	0.17	-0.03	474	815
10	SD35LFSH	El-Fasher	Sudan	25.33	13.62	80	0.43	1.22	1.92	261	638
11	SD30LBD0	El-Obeid	Sudan	30.23	13.17	95	0.32	0.53	0.39	356	719
12	SD28NNHD	En-Nahud	Sudan	28.43	12.70	86	0.28	0.39	1.00	384	687
13	SD20RRHD	Er-Rahad	Sudan	30.60	12.70	54	0.31	0.80	3.21	432	909
14	SD32FSHS	Fashashoya	Sudan	32.50	13.40	43	0.32	0.04	-0.11	297	529
15	SD23GRCL	Garcila	Sudan	23.12	12.35	44	0.30	1.97	6.75	672	1492
16	SD34HWTO	Hawata	Sudan	34.60	13.40	48	0.23	-0.19	1.35	571	953
17	SD22JBLN	Jebelein	Sudan	32.78	12.57	62	0.29	-0.50	-0.40	377	554
18	SD56KSSL	Kassala	Sudan	36.40	15.47	96	0.30	-0.04	-0.18	298	488
19	SD13KBBM	Kubbum	Sudan	23.77	11.78	43	0.27	-0.01	-0.23	646	1013
20	SD44KTM0	Kutum	Sudan	24.67	14.20	62	0.40	0.16	0.28	288	589
21	SD24NYL0	Nyala	Sudan	24.88	12.05	77	0.29	0.11	-0.30	440	778
22	SD12RNK0	Renk	Sudan	32.78	11.75	82	0.20	0.35	-0.09	507	751
23	SD52SHMB	Shambat-Obs.	Sudan	32.53	15.67	81	0.94	2.99	11.31	167	938
24	SD63SHND	Shendi	Sudan	33.43	16.70	54	0.74	1.16	2.08	100	371
25	SD45SHWK	Showak	Sudan	35.85	14.22	40	0.30	-0.22	1.70	473	869
26	SD01TLD0	Talodi	Sudan	31.38	10.60	72	0.23	1.12	3.57	791	1565
27	SD00TLDM	Talodi-M. Ag.	Sudan	30.50	10.60	44	0.21	0.41	-0.35	774	1158
28	SD36MMKD	Umm-Ruwaba	Sudan	26.67	13.58	78	0.32	1.93	9.26	365	983
29	SD78W000	Wau	Sudan	28.02	7.70	87	0.16	0.26	-0.34	1110	1581
30	SD23ZLNG	Zalingei	Sudan	23.48	12.90	59	0.23	0.38	0.17	606	980
31	ET19KMBL	Combolcha	Ethiopia	39.72	11.08	45	0.17	-0.84	0.69	1032	1333
32	ET07DBRM	Debremarcos	Ethiopia	37.72	10.35	45	0.11	0.82	0.59	1335	1769
33	ET84GMBL	Gambela	Ethiopia	34.58	8.25	89	0.22	0.00	0.25	1245	1908
34	ET85GR00	Gore	Ethiopia	35.55	8.17	51	0.20	1.40	2.15	2163	3558
35	ET89WNJ0	Wenji	Ethiopia	39.25	8.42	44	0.28	-0.76	1.92	787	1181
36	EG32SSWN	Asswan	Egypt	32.78	23.97	52	1.92	2.15	3.77	1.2	9
37	EG71SYT0	Asyut	Egypt	31.17	27.20	62	1.95	2.50	5.86	1.9	15
38	EG91HLWN	Helwan	Egypt	31.33	29.87	85	0.72	1.39	2.07	25.7	91
39	EG62QN00	Qena	Egypt	32.72	26.15	52	1.78	2.17	4.11	2.4	18

Long. and Lat.: longitude and latitude in degrees respectively.

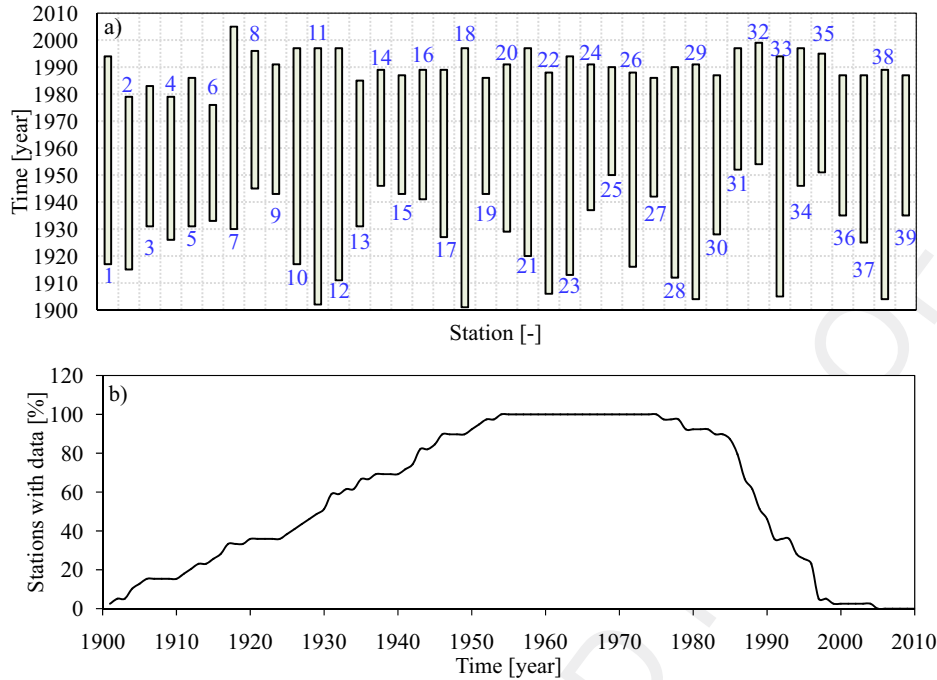
riparian countries (Burundi, Rwanda, Uganda, Kenya, Tanzania, South Sudan, Democratic Republic of Congo (previously known as Zaire), Sudan, Eritrea, Ethiopia, and Egypt) is the world's longest river under arid conditions. In the history of flooding in the NRB, Ethiopia, Tanzania, Kenya, Sudan and Uganda are the most affected countries in terms of the average number of flooding occurrences (Kibiyi et al., 2010). Apart from floods, some areas of the NRB also experience droughts. Although the equatorial region and the Ethiopian highlands receive rainfall in excess of 1000 mm, about 28% of the NRB receives less than 100 mm annually (Onyutha and Willems, 2015a).

Quality controlled long-term monthly rainfall series of length not less than 40 years used by Onyutha and Willems (2015a) were adopted for this study. For the details on the data source, description and analysis, the reader is referred to Onyutha and Willems (2015a). Filling-in of missing values was

by the inverse distance weighted interpolation as implemented in Onyutha and Willems (2015a, 2015b) for the rainfall of the study area.

From the monthly rainfall series, seasonal and annual rainfall intensity totals were obtained for the trend analyses. Table 1 shows for all the stations the coordinates, station name and ID, record length, long-term mean (LTM, mm/year), maximum total (MAX, mm/year), coefficient of variation (C_v), skewness (C_s) and actual excess kurtosis (K_u) of the annual rainfall time series. Whereas stations 1–7 in Eastern Africa are in the equatorial region (EQR), 8–39 in Sudan, Egypt and Sudan (SEE) are more or less in the northern half of the NRB.

Fig. 2a shows the chronograms indicating years with complete monthly data (after filling-in missing values using the inverse distance weighted interpolation). The density of data across the study area over the different years is presented in



1 Fig. 2. Rainfall data characterized by: a) record period and b) variation of number of stations with time (the labels of the stations from 1 to 39 are in the order
2 arranged in Table 1).

3

4 **Fig. 2b.** The percentage of stations (out of a total of 39) with
5 data was low in the early 1900s, followed by a steady increase
6 up to about 1955. This shows that from 1900 to 1955, a number
7 of new meteorological stations were installed. The high number
8 of rainfall stations with available data over the period 1945 to
9 1985 was followed by a rapid drop between 1985 and 2000. One
10 common reason for meteorological stations becoming non
11 operational is the poor maintenance practice. It is only at station
12 7 that data were available after the year 2000 up to 2004.
13 Because the rainfall data are not up to date, the effect of the
14 recent rainfall variation after 2000 on the long-term trend was
15 not captured. However, for an insight into the recent rainfall
16 variation, studies such as Onyutha (2015a, 2015b) which used
17 country-wide gridded monthly rainfall data from the British
18 Atmospheric Data Centre can be consulted.

20 3. Methodology

21 3.1. Trend detection methods

22 To detect trend in the rainfall data, the following steps were
23 taken:

- 24 1) checking whether the data had significant AR(1)
25 process,
- 26 2) in case of significant AR(1) process, TFPW was per-
27 formed and step (1) repeated, and
- 28 3) if the AR(1) process was insignificant, the MK test was
29 conducted and the linear trend slope m computed.

30 The above steps (1)–(3) are briefly described next in sections
31 3.1.1–3.1.3.

3.1.1. Mann–Kendall test

The MK (Kendall, 1975; Mann, 1945) test statistic S is
33 defined as:

$$34 S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (1) \quad 35$$

36 where x_j and x_i are the sequential data values in a sample of
37 size n , and

$$38 \text{sgn}(x_j - x_i) = \begin{cases} 1 & \text{if } (x_j - x_i) > 0 \\ 0 & \text{if } (x_j - x_i) = 0 \\ -1 & \text{if } (x_j - x_i) < 0 \end{cases} \quad (2) \quad 39$$

40 For $n \geq 8$, Kendall (1975) and Mann (1945) have docu-
41 mented that S is approximately normally distributed with the
42 mean $E(S) = 0$ and variance $V(S)$ given by:

$$43 V(S) = \frac{1}{18}(n(n-1)(2n+5)) \quad (3) \quad 44$$

45 In case of tied ranks, $V(S)$ becomes:

$$46 V(S) = \frac{1}{18} \left(n(n-1)(2n+5) - \sum_{k=1}^w t_k(k-1)(2k+5) \right) \quad (4) \quad 47$$

48 where: w is the number of tied groups, and t_k is the number of
49 observations in the k^{th} group.

50 The standardized MK test statistic Z_{MK} which follows the
51 standard normal distribution with mean of zero and variance of
52 one is given by:
53

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{V(S)}} & \text{for } S > 0 \\ 0 & \text{for } S = 0 \\ \frac{S+1}{\sqrt{V(S)}} & \text{for } S < 0 \end{cases} \quad (5)$$

A positive (negative) value of S indicates an increasing (decreasing) trend. The trend is significant if Z_{MK} is greater than the standard normal variate $Z_{\alpha/2}$ where $\alpha\%$ is the significance level.

3.1.2. Computation of linear trend slope

Whereas a trend statistic shows the trend direction, the trend magnitude is in terms of slope m the robust estimate of which is given by (Sen, 1968; Theil, 1950):

$$m = \text{Median} \left(\frac{x_j - x_l}{j - l} \right), \quad \forall l < j \quad (6)$$

where x_j and x_l are the j^{th} and l^{th} observations, respectively.

3.1.3. Pre-whitening procedure

The TFPW procedure (Yue et al., 2002a) follows the procedure described below.

i) By assuming the trend to be linear, m is estimated using equation (6).

ii) The detrended series Y_i is obtained from the given data X_i by:

$$Y_i = X_i - mi \quad (7)$$

iii) The lag-1 serial correlation coefficient r_1 of the detrended series Y_i is computed using (Salas et al., 1980):

$$r_1 = \frac{\frac{1}{(n-1)} \sum_{i=1}^{n-1} [Y_i - E(Y_i)][Y_{i+1} - E(Y_{i+1})]}{\frac{1}{n} \sum_{i=1}^n [Y_i - E(Y_i)]^2} \quad (8)$$

where $E(Y_i)$ is the mean of the Y_i series.

iv) Although r_1 from equation (8) is normally used directly in the TFPW procedure, in this study following the remark of Hamed (2009) and the fact that the ordinary least squares estimates of r_1 are negatively biased (Kendall, 1954), bias corrected r_1 ($r^{\#}$) based on van Giersbergen (2005) is calculated using (Hamed, 2009):

$$r^{\#} = \frac{(nr_1 + 2)}{n - 4} \quad (9)$$

v) The AR(1) is removed from the Y_i series by:

$$Y_i^* = Y_i - r^{\#} Y_{i-1} \quad (10)$$

vi) The linear trend and the residual are combined to form a blended series Y_i^b to which the trend detection test is applied:

$$Y_i^b = Y_i^* + mi \quad (11)$$

3.2. Trends in rainfall of annual and seasonal timescales

The MK test was applied to both annual and seasonal rainfall. The differences between the trend results from the different time scales were obtained graphically by plotting the Z_{MK} values of: (1) one season against those of another, and (2) annual against those of seasonal rainfall.

3.3. Short versus long-term data in trend analysis

To understand the influence of data availability on trend analysis, comparison was made between the Z_{MK} values from the short and long-term data. The full time series at each station was taken as the long-term data. The record length of the rainfall full time series at each station was as already shown in Fig. 2a. From the full time series, short-term data of 20 years' record length were selected. These short-term data covered the period 1940–1959 (for the EQR) and 1960–1979 (for SEE). For the selected period in each region, rainfall data were available at all the stations. The Z_{MK} values for the shorter-term data were also graphically compared with those of the full time series.

To examine the differences between the trend results from the short and long-term data in a temporal way, stations 1, 11, 18 and 33 with rainfall full record lengths above 75 years were used. These stations cover different types of trends in wet and dry seasons across the NRB. For each selected station, trends were assessed in the annual rainfall as well as the March to May (MAM) and June to September (JJAS) seasonal series. By employing the concept of sub-trend identification of Onyutha (2015a), time slices of lengths in the range 20–70 years were passed through the rainfall time series. For station 18, consider the data years 1901, 1902,, 1996; if a Block Length (BL) of, say, 20 years is selected and moved each time by 1 year, the resulting time slices would cover the periods 1901–1920, 1902–1921,, 1977–1996, respectively. The results obtained over the different time slices were used to assess the closeness between the Z_{MK} values from short ($Z_{ST(i)}$) and long-term (Z_{LT}) data records in terms of the bias [%], which represents the mean error:

$$\text{Bias}[\%] = \frac{1}{B} \sum_{i=1}^B \left(\frac{Z_{ST(i)} - Z_{LT}}{Z_{LT}} \times 100 \right) \quad (12)$$

where B is the number of sub-series time slices.

Uncertainty bounds were graphically constructed on the short-term data Z_{MK} values in the form of: (1) 95% confidence interval, (2) range (the difference between maximum and minimum Z_{MK} values), and (3) mean \pm standard deviation of the Z_{MK} values.

3.4. Test of trend homogeneity

The MK test adopted in this study implicitly assumes homogeneity between seasons. Although a trend may be apparent for each season, the overall Z_{MK} , e.g. for annual rainfall, may indicate no trend (van Belle and Hughes, 1984). This can lead to an ambiguous conclusion on the overall change at a station when actually trend between seasons is heterogeneous. Thus, application of a homogeneity test (van Belle and Hughes, 1984) is

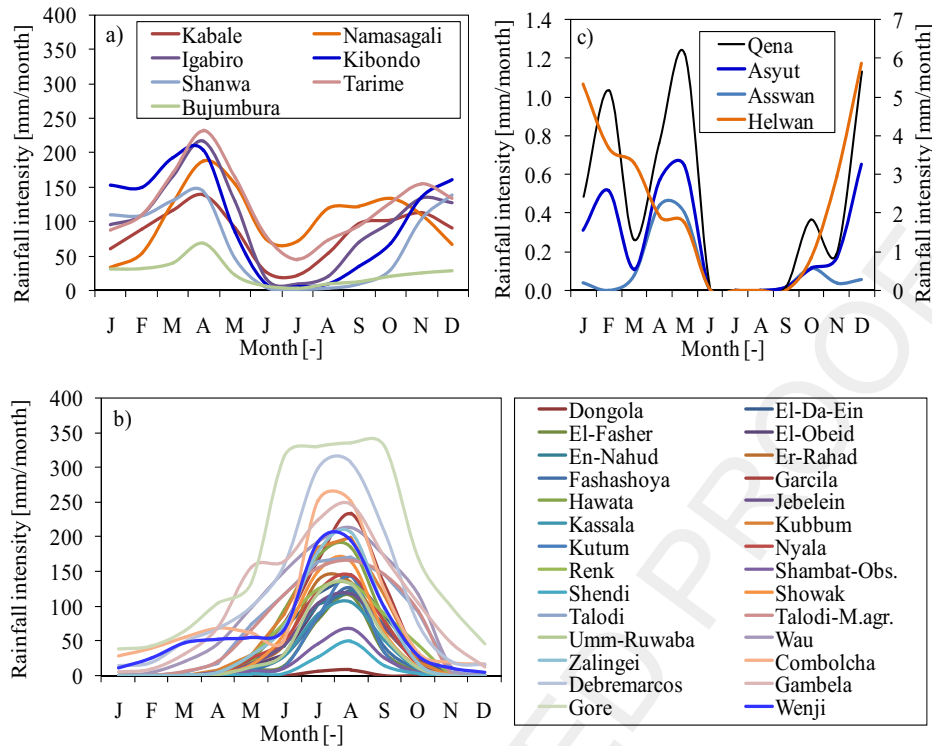


Fig. 3. Long-term mean monthly rainfall for a) the EQR, b) Sudan and Ethiopia, and c) Egypt; for clarity, the dataset for Helwan is presented on the secondary y-axis in chart (c) (Source: Onyutha and Willems, 2015a).

useful to combine data from the different seasons to obtain a single global trend. The homogeneity of seasonal trends was evaluated based on the χ^2 test with statistic:

$$\chi_{\text{homogeneous}}^2 = \chi_{\text{total}}^2 - \chi_{\text{trend}}^2 = \sum_{i=1}^q Z_{MK}^2(i) - q(\bar{Z}_{MK})^2 \quad (13)$$

$$\bar{Z}_{MK} = \frac{1}{q} \sum_{i=1}^q Z_{MK}(i) \quad (14)$$

where q is the number of seasons at the station under consideration.

The null hypothesis H_0 of homogeneous trend in seasons, i.e. ‘the trends are in the same direction’, is used to obtain two results: (1) If $\chi_{\text{homogeneous}}^2$ exceeds the critical value for the chi-square distribution of $(q-1)$ degree of freedom (df), H_0 is rejected; (2) If $\chi_{\text{homogeneous}}^2$ does not exceed the critical value for the chi-square distribution of $(q-1)$ df , the value of χ_{trend}^2 is the chi-square distribution with $df=1$ used to test H_0 , i.e. ‘the common trend direction is significantly different from zero’.

The van Belle and Hughes test was applied to two cases: firstly, when the data (full series) of all the meteorological stations were of unequal record length while covering the different time periods, and secondly, when the data record length as well as the time period were the same for all the stations (30-year period, i.e. 1951–1980 over which about 95% of the stations had data). Comparison was made between the van Belle and Hughes test results from the first and the second case. This was to investigate the influence of different data record lengths

on the homogeneity of trend results in a region. The idea is that, if the rainfall trends are homogenous, an insightful support for the trend in short-term series can be obtained from the trend in long-term data at another neighboring station within the same region.

4. Results and discussions

4.1. Spatial differences in rainfall statistics

Fig. 3 shows long-term mean monthly rainfall pattern for the selected stations. It is shown that the rainfall in the EQR (stations 1 to 7) exhibits a bimodal pattern with the main wet season in MAM and ‘short rains’ in October to December (OND) (Nicholson, 1996). Two dry seasons exist as well; the main one is in JJAS and the other from January to February (JF). Contrastingly, as shown in Fig. 3b, the JJAS period is main wet season in Sudan and Ethiopia (stations 8 to 35) and ‘short rains’ are in MAM. There is one long dry season from October to February (ONDJF). For Egypt, the mean value of rainfall in each month is far lower than those in Sudan, Ethiopia and the EQR (Fig. 3c) (Onyutha and Willems, 2015a). According to Camberlin (2009), large variations in long-term mean rainfall statistics across the NRB are due to its great latitudinal and longitudinal extents.

Fig. 4 shows the annual rainfall time series of some stations selected for illustration purpose. For the EQR (Fig. 4a–c), there was the tendency of the annual rainfall at stations 1, 5, and 7 to increase with time. Contrastingly in Fig. 4d–j, for Sudan (station 9, 11, 18, 21, 26), Ethiopia (station 33) and Egypt (station 38), the annual rainfall was decreasing.

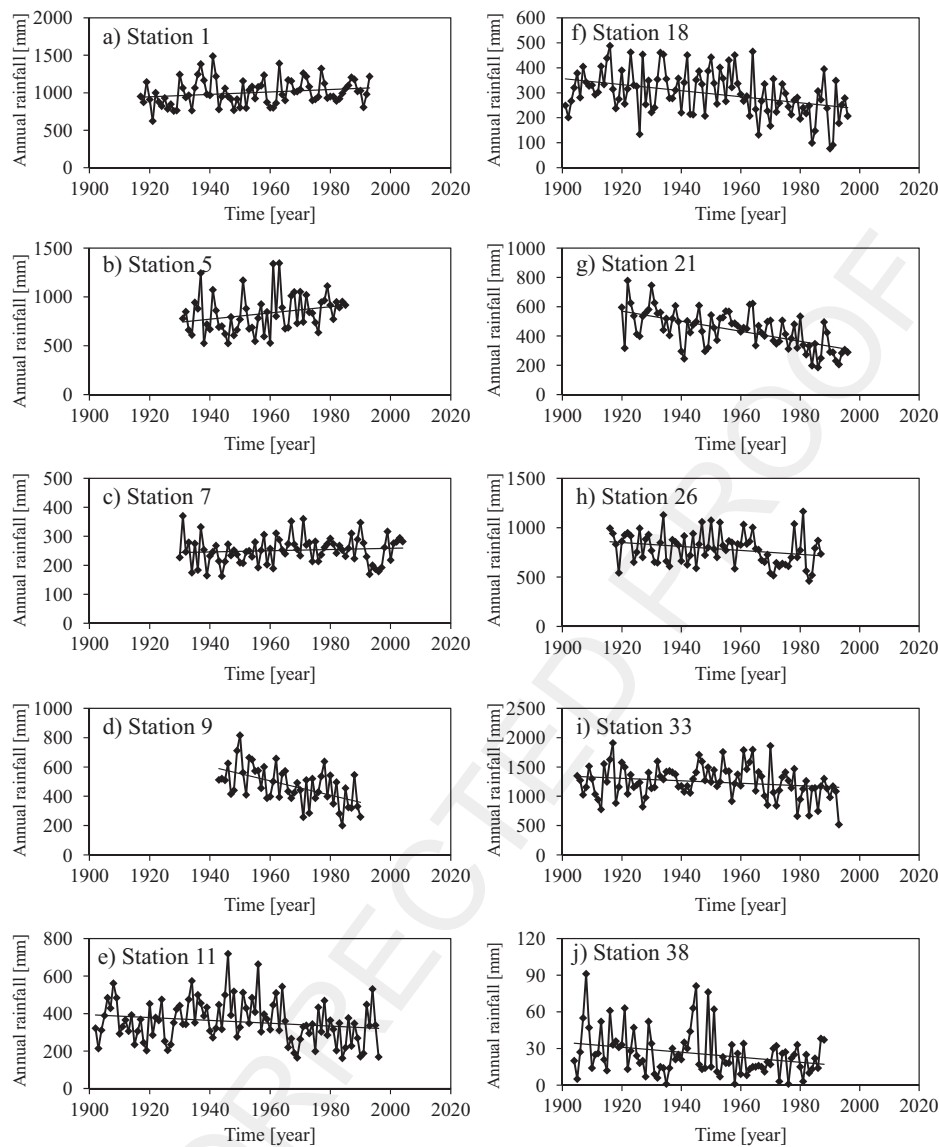


Fig. 4. Linear trends in annual rainfall at selected stations.

4.2. Trend results

Fig. 5 shows trend results for the OND season in the EQR. The threshold levels for Z_{MK} at a significance level $\alpha = 5\%$ is $+1.96$ and -1.96 . The r_1 values in Fig. 5b fell within the confidence interval limits; thus the AR(1) process was insignificant and the OND rainfall trend was analyzed without performing TFPW. Significant upward trends occurred in the OND rainfall at stations 1, 5 and 6 (Fig. 5a). However, a decrease (though not significant) was obtained in rainfall at station 4. The trend results for annual and seasonal rainfall were summarized in Table 2.

From Table 2, the annual rainfall showed significant trends in 56% of the 39 stations. In the EQR (stations 1 to 7), trends were mainly positive and significant in 57% of the stations. Positive trends (though not all significant) in the annual rainfall of the Lake Victoria basin located in the EQR were also found by Conway and Hulme (1993), Kizza et al. (2009), and

Nyeko-Ogiramoi et al. (2013). In the northern half of the NRB or SEE (stations 8 to 39), the annual rainfall trends were mainly negative and significant in 69% of the stations. Slightly-to-strongly decreasing trends in rainfall in this part of the NRB were also reported by Conway and Hulme (1993). Furthermore, Seleshi and Zanke (2004) also documented the evidence of a significant decline in annual rainfall in the Southwest of Ethiopia.

For the entire NRB, significant trends at $\alpha = 5\%$ were in 31% and 46% of the 39 stations for MAM and JJAS season respectively. For the MAM rainfall, significant negative (positive) trends at $\alpha = 5\%$ were found in 8% (23%) of the stations. Correspondingly, 3% (44%) was obtained for the JJAS rainfall. Decreasing JJAS rainfall trends significant at $\alpha = 5\%$ were found in 15 (2) stations in Sudan (Ethiopia). Wing et al. (2008) also found significant decline especially in the JJAS rainfall in the Southern Blue Nile watersheds located in the southwestern and central parts of Ethiopia. Decreasing ONDJF rainfall trends

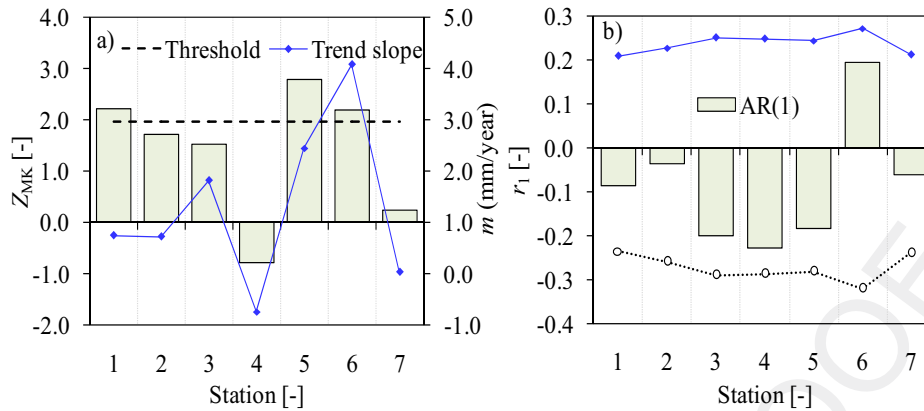


Fig. 5. Results of (a) MK test, and (b) AR(1) analysis for OND rainfall in the EQR; UL and LL are the upper and lower limits of the confidence interval (CI) at 5% significance level.

Table 2
Statistical results of trend analysis for annual and seasonal rainfall.

SNo.	Station name	Annual rainfall		MAM season		JJAS season		JF ⁽¹⁻⁷⁾ or ONDJF ⁽⁸⁻³⁹⁾	
		Z_{MK}	m	Z_{MK}	m	Z_{MK}	m	Z_{MK}	m
1	Kabale	2.25*	1.93	1.31*	0.56	0.58	0.22	-0.03	-0.02
2	Namasagali	3.51	4.44	1.65	1.08	2.09	1.00	2.56	0.75
3	Igabiro	1.66	4.85	2.01	2.59	0.35	0.21	0.49	0.40
4	Kibondo	0.25	0.36	0.80	1.00	1.07*	0.59	-0.08	-0.10
5	Shanwa	2.35	3.61	0.32	0.31	0.65*	0.08	-0.01	0.02
6	Tarime	2.52*	7.92	0.77	1.38	0.77	0.71	1.82	1.80
7	Bujumbura	1.42	0.29	1.00	0.11	1.08*	0.12	-0.43*	-0.06
8	Dongola	-1.93	-0.17	0.70	0.00	-2.12	-0.11	0.00	0.00
9	El-Da-Ein	-3.55	-4.52	-0.93	-0.18	-2.95	-3.93	-2.10	-0.49
10	El-Fasher	-4.25	-1.90	-0.33	0.00	-4.16	-1.87	-0.47*	0.00
11	El-Obeid	-2.11	-0.85	-0.88	-0.03	-1.63	-0.69	-0.81	-0.02
12	En-Nahud	-1.63*	-0.80	-0.73*	-0.06	-1.20	-0.50	-0.31	0.00
13	Er-Rahad	-2.71	-2.89	-2.98	-0.35	-2.17*	-2.30	-2.03	-0.30
14	Fashashoya	-0.98	-1.25	0.20	0.00	-0.85	-0.93	-2.25*	-0.12
15	Garcila	-4.46	-7.57	-2.04	-0.86	-3.82	-6.38	-0.86	-0.21
16	Hawata	-2.37*	-3.28	-1.08*	-0.16	-2.15	-2.50	-0.42	0.00
17	Jebelein	-4.17	-3.25	-2.52	-0.26	-3.83*	-2.79	-1.72*	-0.19
18	Kassala	-3.45*	-1.15	-0.44*	-0.02	-3.58	-1.17	1.17	0.00
19	Kubbum	-3.21	-7.30	-1.00	-0.37	-3.03	-6.12	-1.76	-0.32
20	Kutum	-4.28	-3.46	-2.27	0.00	-4.08	-3.37	0.43	0.00
21	Nyala	-5.63	-3.65	-2.32	-0.27	-5.02	-3.09	-1.03	-0.02
22	Renk	-1.17	-0.60	-1.33	-0.16	-0.45*	-0.16	-1.04	-0.13
23	Shambat-Obs.	-1.36*	-0.62	2.01*	0.01	-1.70*	-0.68	-1.31*	-0.02
24	Shendi	-3.02	-1.81	-1.50	0.00	-3.21	-1.89	1.25	0.00
25	Showak	-0.82	-1.32	2.84	0.50	-1.34	-2.25	2.20	0.28
26	Talodi	-2.61	-2.62	-2.68	-0.92	-1.84	-1.56	-0.08	-0.02
27	Talodi-M. Ag.	-3.02	-6.19	-2.40	-1.79	-2.17	-3.28	-0.54	-0.42
28	Umm-Ruwaba	-2.35	-1.00	-0.64	0.00	-1.97	-0.91	-0.82	0.00
29	Wau	-0.22	-0.12	-1.15	-0.37	0.37	0.24	-0.84	-0.23
30	Zalingei	-3.46	-2.85	-0.52	-0.11	-3.01*	-2.56	-0.93	-0.08
31	Combolcha	-1.60	-2.92	1.42	1.39	-2.20	-3.86	-0.75	-0.40
32	Debremarcos	-2.02	-2.62	1.21	1.31	-1.84	-2.45	-1.94	-1.65
33	Gambela	-1.64	-1.81	-1.98	-0.80	-1.34	-1.13	-0.17	-0.06
34	Gore	-2.82*	-8.73	-1.95	-2.34	-2.22*	-5.00	-1.76*	-2.41
35	Wenji	0.42	0.76	0.43	0.33	0.06	0.31	0.04	0.12
36	Asswan	-1.87	0.00	-1.37	0.00	-0.06	0.00	-0.78	0.00
37	Asyut	-1.79	0.00	0.55	0.00	0.16	0.00	-2.12	0.00
38	Helwan	-1.80	-0.14	-2.50*	-0.01	0.27	0.00	-0.94	-0.06
39	Qena	-1.35	0.00	0.83	0.00	0.20	0.00	-2.12	0.00

The Z_{MK} marked with * is obtained after TFPW procedure from series with AR(1) significant at the 5% level; the values of Z_{MK} significant at the 5% level are shown in bold.

JF⁽¹⁻⁷⁾: JF season of stations 1-7; ONDJF⁽⁸⁻³⁹⁾: ONDJF season of stations 8-39.

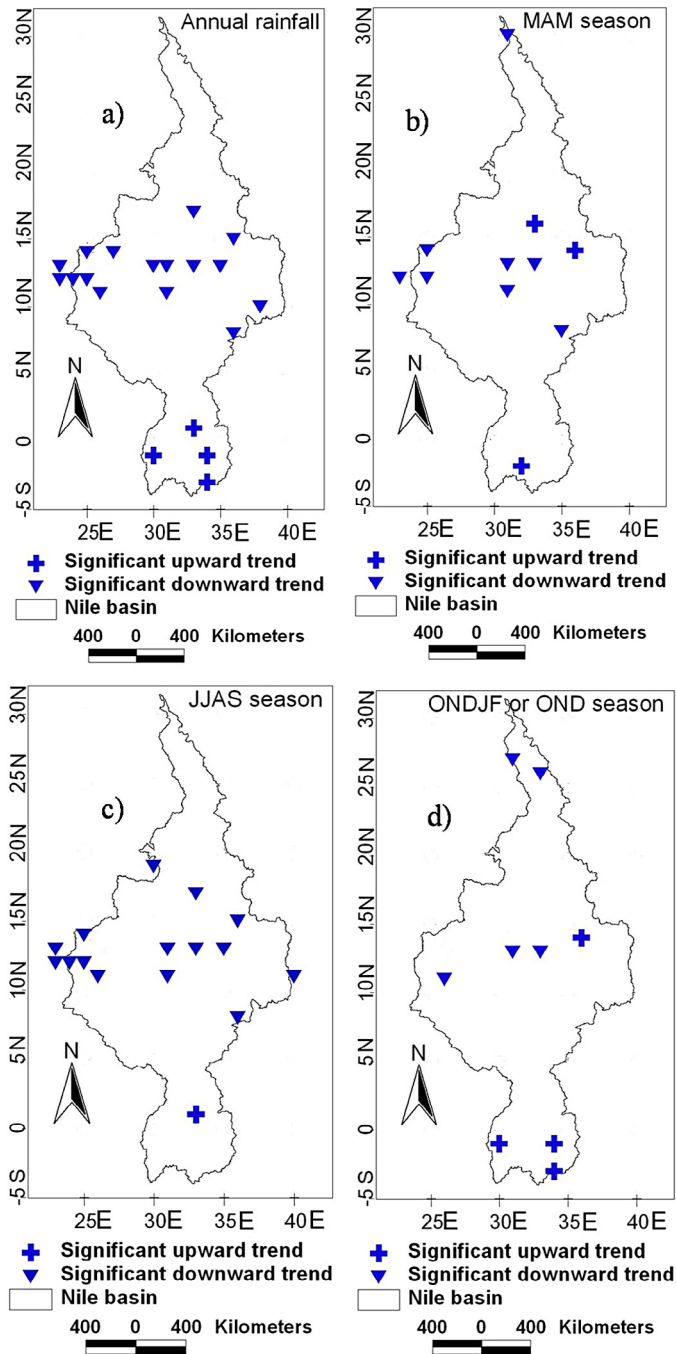


Fig. 6. Spatial variation of rainfall trends at the annual and seasonal scales.

significant at $\alpha = 5\%$ were found in 2 (3) stations in Egypt (Sudan). At $\alpha = 5\%$, increasing trend in the JF rainfall of the EQR was found at one station. The spatial distributions of the stations with significant trends for annual rainfall as well as the MAM, JJAS, OND and ONDJF series are presented in Fig. 6. Because the JF rainfall trend was significant only at station 2, no map was presented for this season. It was noted that rainfall was increasing in some seasons and decreasing in others (Fig. 7). Moreover, the annual rainfall trends were also different from those of the seasonal time scales. This means that the possible drivers of trends in annual and seasonal rainfall may be

different. The causes of rainfall trend may also vary from one season to another. However, for the EQR (SEE), out of the 4 (17) stations with significant upward (downward) annual rainfall trend, 3 (15) also showed similar results in the OND (JJAS) season. This observation can be confirmed from Fig. 7b and c for the SEE and EQR respectively where the scatter points fairly fall along the 45° (bisector) line on the Cartesian coordinates. This suggested that trend in annual rainfall in the EQR (SEE) is caused by variations in the OND (JJAS) season. Validity of the trend directions in the different seasons was confirmed using the homogeneity test as presented next.

4.3. Test of trend homogeneity

Fig. 8 shows homogeneity test results for rainfall trend directions of the different seasons. This test required two steps; firstly, based on the number of seasons $q = 4$ (3) for EQR (SEE), $\chi^2_{\text{homogeneous}}$ was compared at $\alpha = 1\%$ with its critical value of 11.34 (9.21) (Fig. 8a). The H_0 was rejected at stations 10, 18, 20, 24 and 25 (i.e. 5 out of 39 or 13% of the stations). This indicated the presence of significant up or downward trend in some (if not one) of these seasons. This was confirmed using trend results (Table 2) for the JJAS rainfall (stations 10, 18, 20 and 24) and MAM series (station 24).

Secondly, using Fig. 8b, by comparing χ^2_{trend} with its critical value (6.63 using $df = 1$ at $\alpha = 1\%$), rainfall trend directions in some (if not all) of the seasons were confirmed to be significantly different from zero at stations 2, 9–10, 13, 15, 17, 21, 26–27 and 34 (i.e. 28% or 11 out of the 39 stations). This meant that significant trends would be obtained from annual rainfall (as confirmed in Table 2) when data from all the seasons at each of these stations were combined. In each of the remaining stations (those below the critical value), the common trend direction was not significant. This explains why, when all the seasons were combined, the annual rainfall trends for these stations were insignificant.

Because of the possibility of rainfall from different season to different trend directions, the ONDJF rainfall (see Table 2) had positive trend (though not significant at $\alpha = 5\%$) and while the JJAS (MAM) season was characterized by a significant (insignificant) decreasing rainfall. These positive and negative effects cancel out each other in the trend result from data obtained by combining the series with opposite trend directions. Consequently, the overall trend in the annual rainfall at a station is typical of the net cancellations of the trend effects from the seasonal series. Revealing this kind of seasonal effects hidden by the annual scale analysis was deemed valuable for management plan of water resources.

Generally for the different seasons, the magnitudes (and sometimes the signs) of the trends in rainfall varied from one station (or NRB sub region) to another. This might have been due to high noise to signal ratio or difference in microclimate (micro-scale features). Even for a given station, the magnitudes (and sometimes the signs) of rainfall trends varied from one season to the next. This suggested that drivers of the rainfall trends might differ per season and hence trend results as well. The differences in trend results across sub regions could have some connection with the influence of regional features

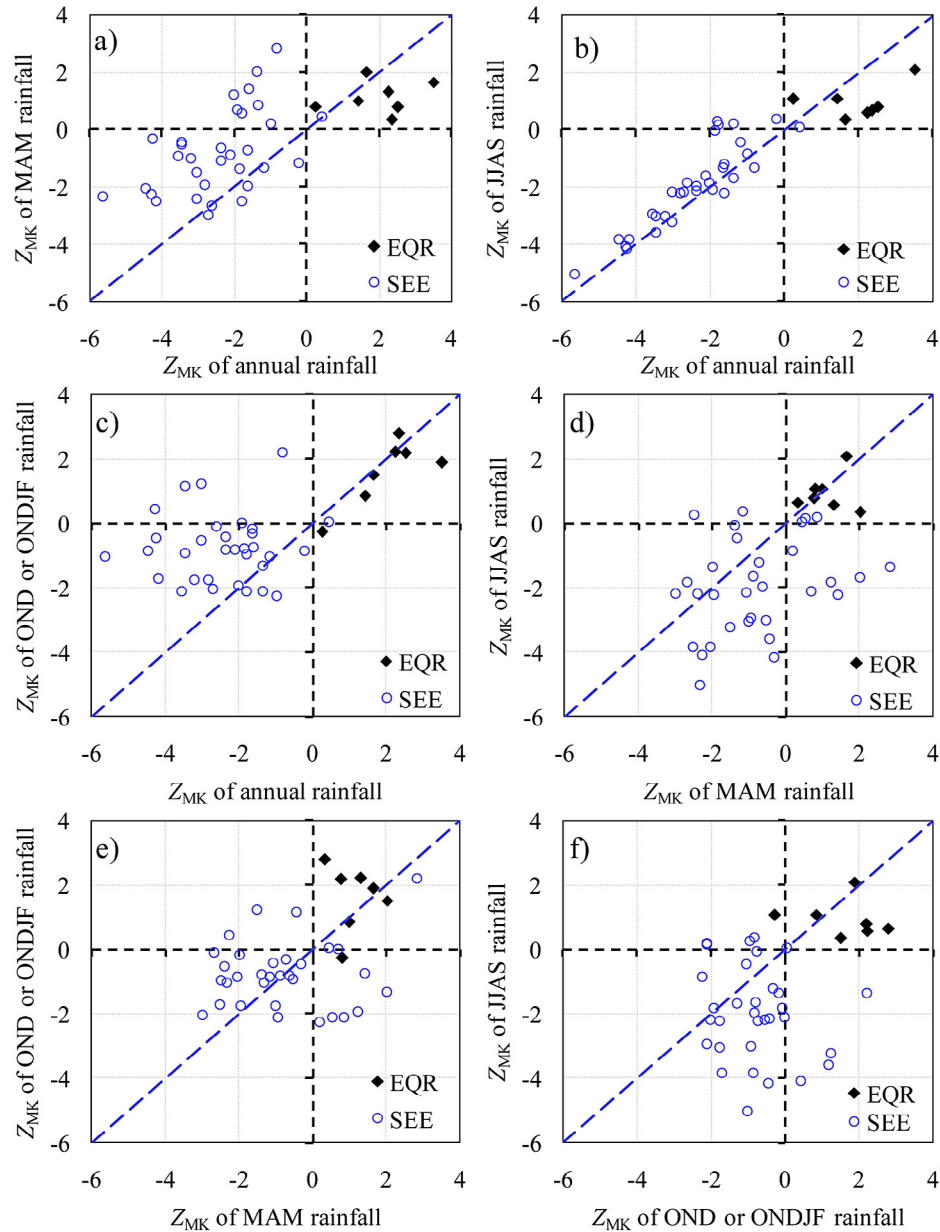


Fig. 7. Variation of rainfall trends at the annual and seasonal scales; Z_{MK} stands for the standardized MK trend statistic.

(topography, water bodies, land cover etc.) over atmospheric circulation. As a result, variations in the wet and dry seasons may become apparent. The highlands which bound the NRB to the east, from Eritrea to Kenya, restrict penetration of the easterlies from the Indian Ocean; an exception is the gap between the Ethiopian and Kenyan Highlands (Camberlin, 2009). Furthermore, the highlands of the Rift Valley also block the moist, unstable westerly flow of the Congo air from reaching the coastal areas (especially of Ethiopia) leading to a complex pattern of rainfall over the Ethiopian highlands (Nicholson, 1996). Furthermore, the East African Great Lakes tend to develop their circulation in the form of lake breezes which interact with slope circulation (Camberlin, 2009). The joint impact of these lake and upslope breezes is the afternoon convection. Quantifying these regional influences due to topogra-

phy over atmospheric circulation would be important. This, though not done in this study, can be carried out by regional climatic modeling while taking into account local topographical features alongside the three-dimensional lake dynamics.

4.4. Short versus long-term trends

Fig. 9 shows the effect of data record length on the trend result. Due to non-stationarity in the climate system, the long-term trend may systematically differ from the short-term trend. Although short-term data may be used to get an insight into the evolution of the long-term trend, results from them might sometimes not be representative and conclusive. The power of the MK test to detect monotonic trends increases as the sample size (data record length in this case) becomes larger (Yue et al., 2002b). Apart from the need to use long-term data, the

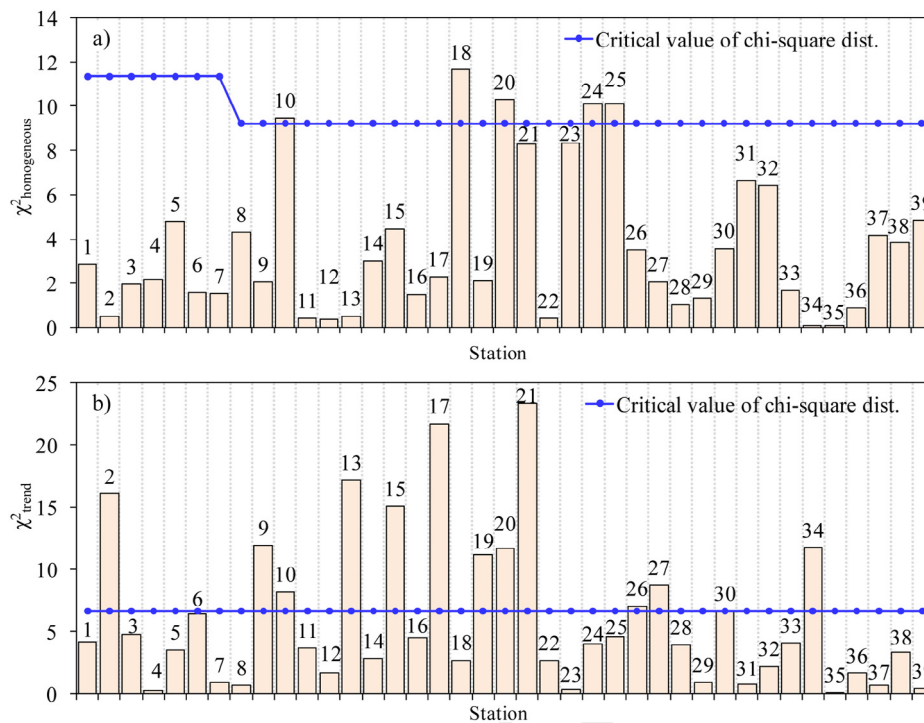


Fig. 8. Results of Van Belle and Hughes test using full rainfall series (all seasons combined); the labels of the stations from 1 to 39 are in the order arranged in Table 1.

uniformity of the data time period for the selected stations also influences the homogeneity test results.

Fig. 10 shows the uncertainty bounds and bias obtained on the trend results when data of short-term records are used for analysis. As the data record length was increased, the 95% confidence interval (CI) became narrower, the mean of the short-term data trend results (Z_{MK} values) got closer to those of the long-term series (Fig. 10a–d), and the absolute bias [%] became smaller (Fig. 10e–h). It was realized that by increasing the short-term data record length, the rate of decrease in bias [%] on the trend results were non-uniform. For instance, by assuming a linear decrease (for simplicity), it was noted that for every 10% increase in the short-term data record length in comparison with the full series over the periods of 77, 95, 96 and 89 years at stations 1, 11, 18 and 33, the bias on the trend result reduced by 8.72, 12.68, 10.62, 8.12%, respectively. This difference (though not significant) in the bias reduction rates showed the site to site or regional difference in the rainfall statistics across the NRB.

One way to obtain an insight into the rainfall trend under data scarcity is to make use of the possible drivers of the trend and/or variability. However, the results of such an approach would be promising if the causes of rainfall trend is well-known at station-based scale. For the study area, the driving forces of rainfall trend/variability have been investigated mostly on rather regional than station-based scale. The regional rainfall trend/variability in the study area has been found linked to: (1) the Southern Oscillation Index and/or the El-Niño Southern Oscillation (see among others, Abteu et al., 2009; Nicholson and Entekhabi, 1986), (2) the Atlantic Multidecadal Oscillation

index, Pacific Decadal Oscillation Index, and Indian Ocean Dipole (Nyeko-Ogiramoi et al., 2013; Onyutha, 2015b; Taye and Willems, 2012), and (3) the influences of the Oceans through changes in the Sea Surface Temperatures or Sea Level Pressures (Lyon and DeWitt, 2012; Onyutha and Willems, 2015a; Tierney et al., 2013). The above drivers of rainfall trend/variability may be used to get an idea on the directions of trends within a particular region (not at a station-based level) of the study area.

Another alternative to support trend results from short-term rainfall is to use long-term data from a nearby station if available. This, as will be discussed in section 4.5, also requires the acceptability of the homogeneity of the trend directions in the particular region.

4.5. Spatial coherence of trend results

Fig. 11 shows the van Belle and Hughes test results for short-term data. It is shown in Fig. 11a that H_0 (common trend direction in the different seasons) was rejected only at station 30 (1 out of 39 i.e. 2.5%) instead of the 13% for the full time series in Fig. 8a. Moreover, the number of stations with common trend direction characterizing significant increase in rainfall in the EQR was reduced from 2 to only 1 out of 7. For the SEE, the percentage of stations with significant downward trend increased from 34% to 50%. These results confirm that if all the stations across the study area have data with similar record length and time period, an improved coherence of regional trend results could be obtained. For the study area, the above findings showed that support for an inference of trend from short-term rainfall can be moderately acceptable from the result in the

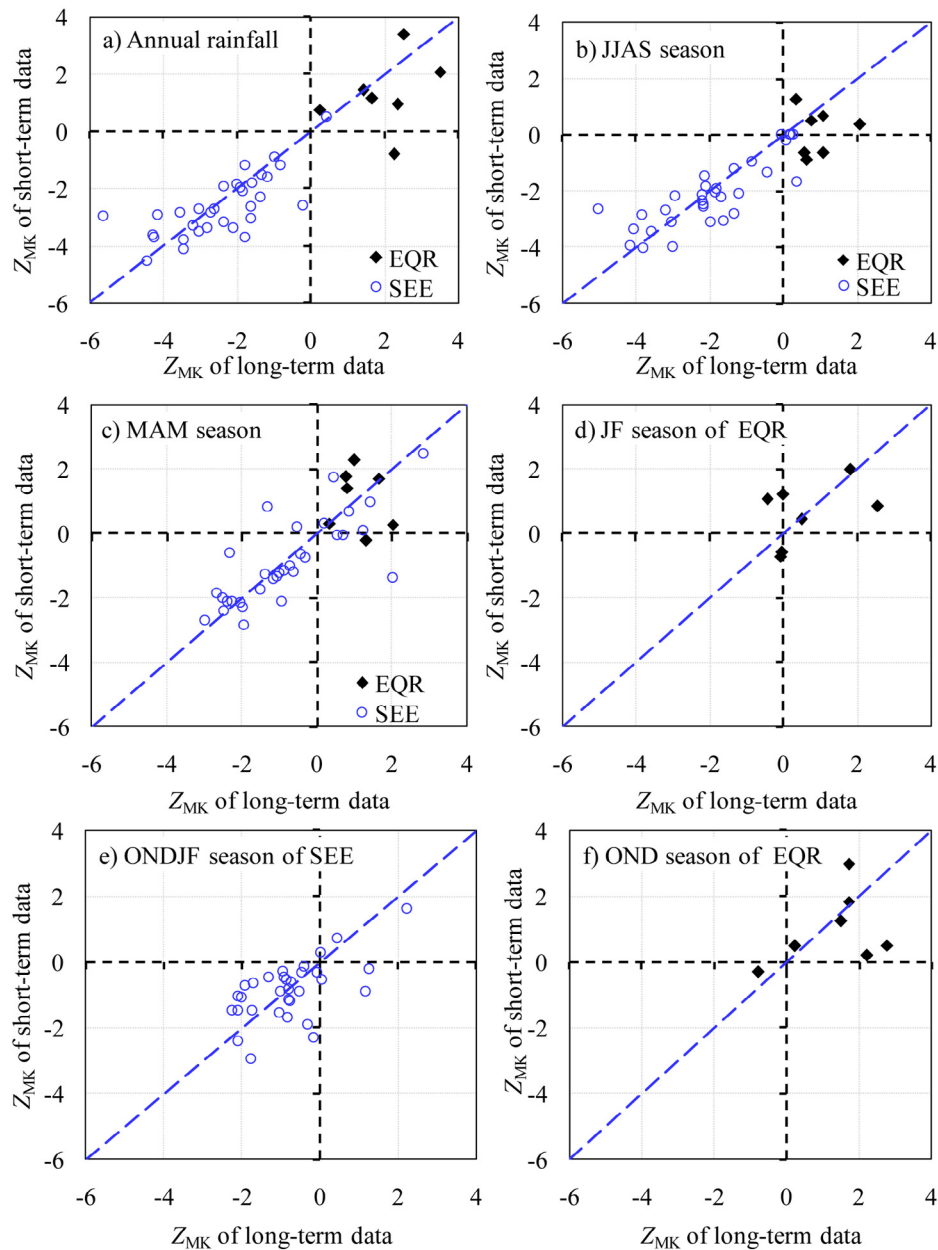


Fig. 9. Comparison of the trend results for short- and long-term rainfall series of annual and seasonal time scales. The long-term data were the full time series as shown in Fig. 2a. From these full time series, short-term data of 20 years' record length covering the period 1940–1959 (for EQR) and 1960–1979 (for SEE) were selected. For these 20-year periods, rainfall data were available at all the stations. Z_{MK} stands for the standardized MK trend statistic.

long-term data at another nearby station within the same region, so long as the same time period from both series is considered. For illustration, the temporal variation of annual rainfall at stations 26 and 27 with data over the periods 1916–1987 and 1942–1985, respectively, is shown in Fig. 12. The close agreement between the pattern of variation from the short- and long-term rainfall data at stations 26 and 27 (Fig. 12), respectively, can be evident. Over the period 1942–1985, the correlation between the annual rainfall at the two stations was 0.89 and thus significant at $\alpha = 1\%$. It is deemed that due to the site to site difference across the study area, the smaller the distance between the station with short- and long-term data, the more reliable the support may be for the inference on trend using short-term rainfall series.

Fig. 13 and Fig. 14 show the trend evolution in annual rainfall as well as that for the MAM and JJAS seasons. For a complete picture of the temporal trend evolution, the Z_{MK} values are plotted against the ending year of the time slices. Compared with the long-term trend (LTT), different results were obtained in most periods for the different Block Lengths (BLs). In some cases, results from short data periods showed decreasing trends while that of the LTT was an increasing one, and vice versa. It has been remarked by Camberlin (2009) and Di Baldassarre et al. (2011) that the trend analyses from different studies on rainfall over the NRB provide conflicting evidence, e.g. for Ethiopia. This study confirmed that trend results depend on the data record length and the time period selected for analyses.

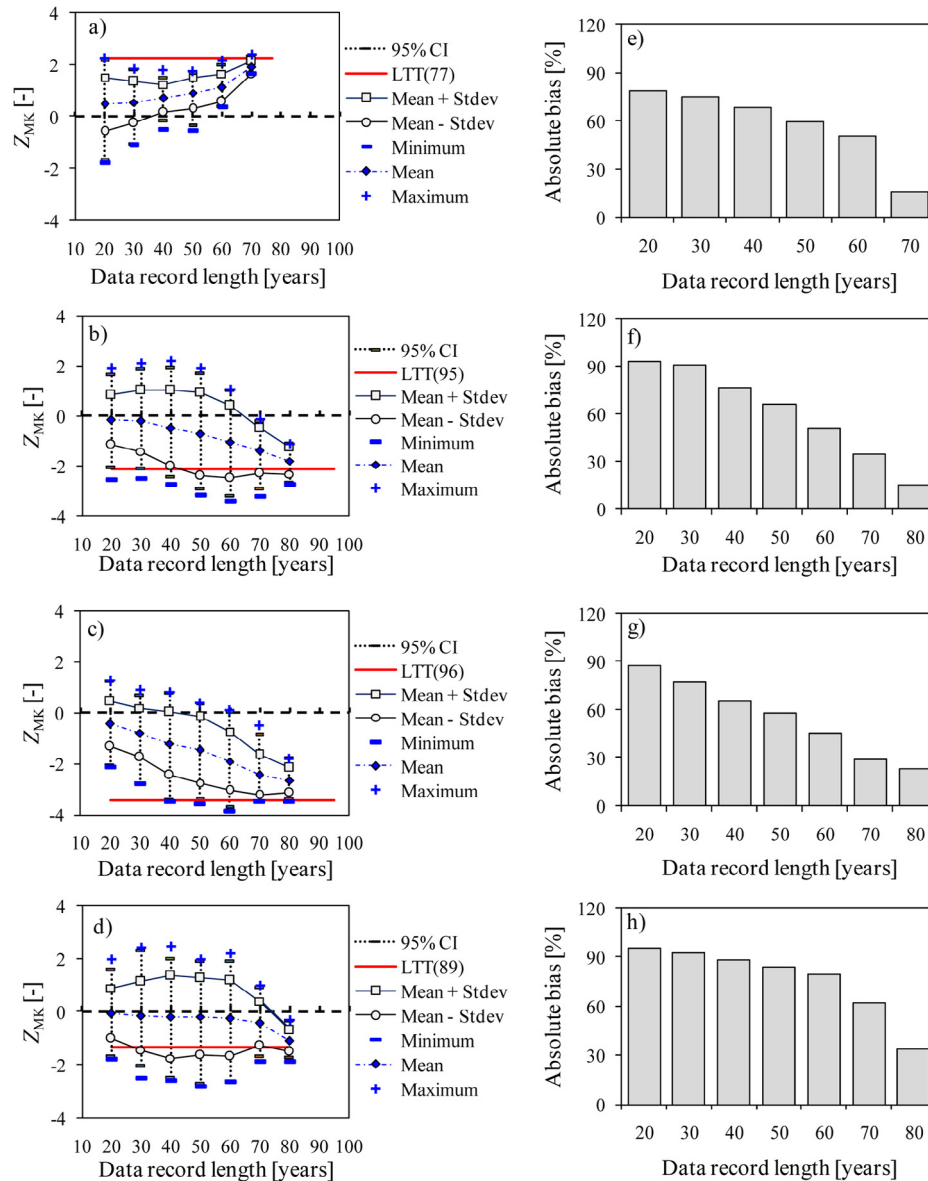


Fig. 10. Maximum, mean, minimum and 95% confidence interval (CI) (a–d) and associated bias (e–h) on the trends in annual rainfall at stations (a, e) 1, (b, f) 11, (c, g) 18, and (d, h) 33. In the legends, Stdev stands for standard deviation, and e.g. LTT(96) shows long-term trend in data recorded over 96 years. Z_{MK} stands for the standardized MK trend statistic.

On the long-term, the effects of the temporal oscillations may cancel out and the overall long-term trend characterizes the net effect of such cancellations (Onyutha, 2015a). Due to the temporal oscillations, it was suggested by the WMO (2000) that climate change detection be investigated using a minimum of 50 years of record. In this study, even when a BL of 70 years was considered from a 95-year rainfall data, there was still some difference based on the period over which the window was passed. As long as we rely on samples, which is always the case for climatic variables, the trend estimates should not be expected to be a true value (of course, we cannot know what the true value is). However, the longer the series, the better the trend estimates. Therefore, importantly the period referred to as the so-called ‘long-term’ is so subjective that the question of what data record length gives bias-free trend results cannot be

clearly answered. This is because it would require specification of the baseline period to be used for assessing bias in the trend of the short-term data being analyzed. This baseline period, which may change over time, can only be set based on a universally clued-up decision of stakeholders. For instance, the widely used baseline period 1961–1990 for climate studies was recently recommended by the WMO (2014) to be shifted because global warming is increasingly setting a new “normal” for weather conditions. With respect to the sub-trend identification (Onyutha, 2015a) implemented in this study, an idea can also be obtained on the pattern of the temporal variability in the series. For instance, in Sudan where stations 11 and 18 were selected, the drastic and significant decrease in the rainfall in the late 1960s to mid 1980s can be noticed from Fig. 13b–c for annual rainfall, Fig. 14b–c for MAM season, and Fig. 14f–g for

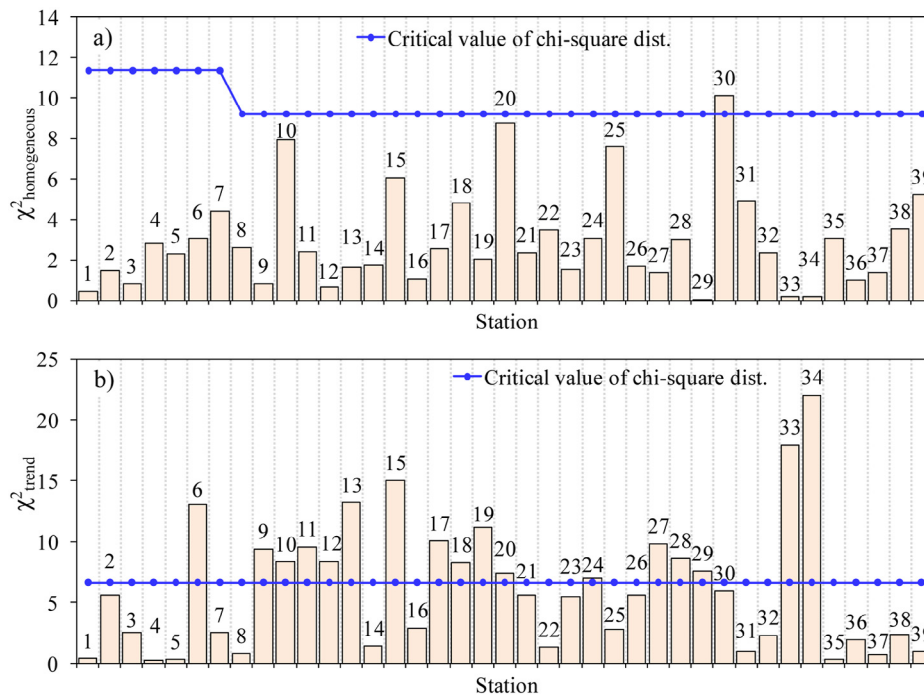


Fig. 11. Results of the Van Belle and Hughes test for time series of equal record length at all the stations; the labels of the stations from 1 to 39 are in the order arranged in Table 1.

JJAS season. In line with this decrease, Hulme (1992) reported that the mean annual rainfall in the Sahel region (which spans across Central Sudan) for the periods 1970s and 1980s declined by 30%. Contrastingly, for station 1 in the EQR, the period 1960s to 1980s was characterized by increase in its rainfall as seen from Fig. 13a for annual rainfall, Fig. 14a for MAM season, and Fig. 14e for JJAS season.

5. Conclusions

In this paper, the following were done: (1) investigation of how data record length and selected time period influence trend results, (2) assessment of bias in trend results due to short-term data record length, (3) investigation of the rainfall trend homogeneity by applying the method of van Belle and Hughes (1984), and (4) determining rainfall trend at 39 locations across the NRB. The main findings from this study include the following:

- Trend results are influenced by the length of the time series and, the period over which the data are selected for analysis; for instance, the negative trends in the stations in SEE were due to the significant decrease in rainfall between the 1960s and 1980s. Because of the bias in trend results, analyses from short-term rainfall data to get an insight into the evolution of the long-term trend might sometimes not be representative and conclusive. For the case of the NRB, by assuming that the rainfall series recorded over 90 years is adequately long and representative of the population, reducing the rainfall data record length by 10% leads to an increase by about 10% as well of the absolute bias on the trend result. To address the possible problem of bias in the trend at a station due to short data length, support can be possibly obtained from another nearby station with long-term data. To obtain this support, regional homogeneity of the rainfall trends is required.
- It still remains unclear which data record length gives bias-free trend results, unless a baseline period is specified.
- The magnitudes (and sometimes the signs) of the trends in rainfall varied from season to season, and also from one station (or sub region) to another. At a given station, trend from annual rainfall data tended to differ from those of the seasonal series. Thus, the rainfall trends' driving forces can differ at annual and seasonal time scales, as well as between seasons. For a given time scale (annual or seasonal), using the same data record length and uniform time period obtained from all the selected stations led to an improved regional coherence (homogeneity) of trend results. Trends for the different rainfall seasons were heterogeneous in 13% of the 39 stations used in this study.

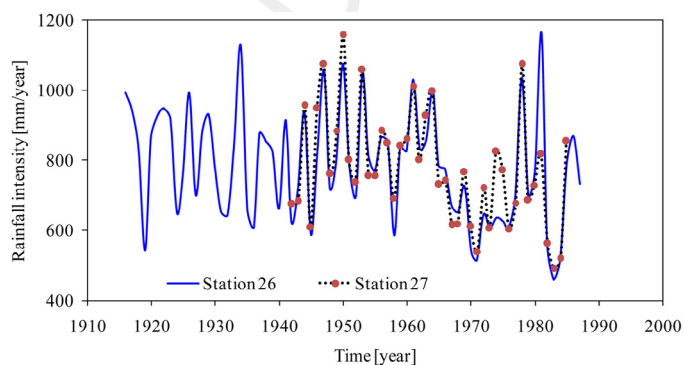


Fig. 12. Annual rainfall at two selected nearby stations in Sudan.

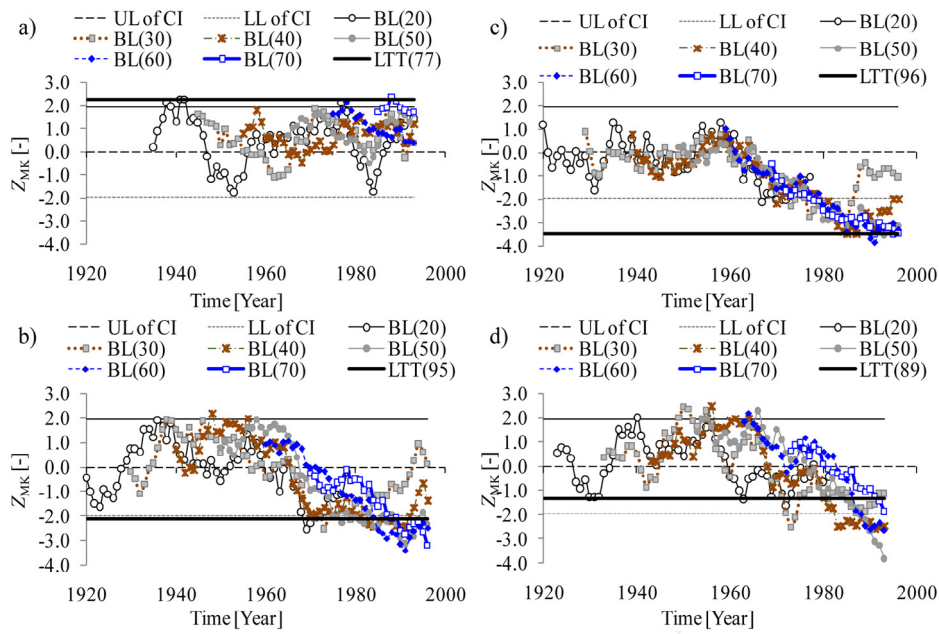


Fig. 13. Results of trends in annual rainfall at stations a) 1, b) 11, c) 18, and d) 33. In the legends, e.g. BL(30) is a 30-year block length, and LTT(77) shows long-term trend in data recorded over 77 years.

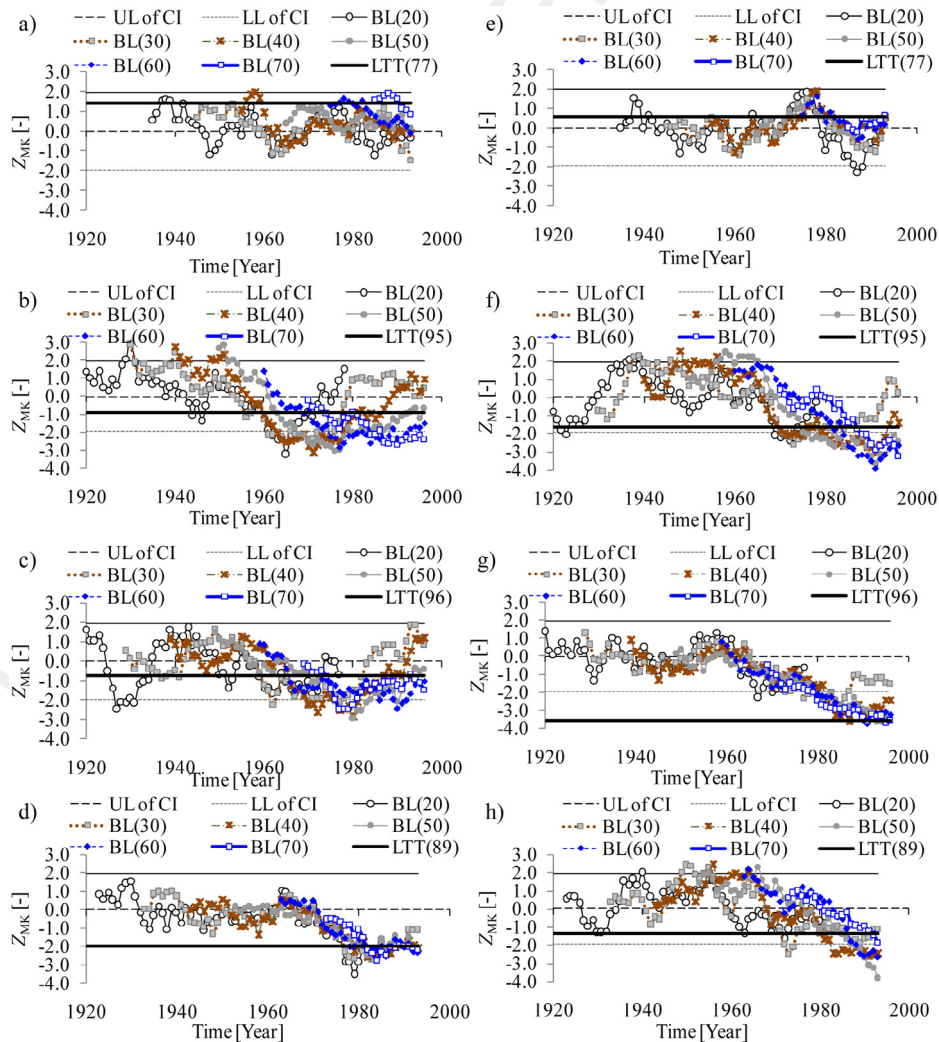


Fig. 14. Results of the trends in seasonal rainfall at stations (a, e) 1, (b, f) 11, (c, g) 18, and (d, h) 33. Charts (a)–(d) and (e)–(h) are for MAM and JJAS seasons, respectively. In the legends, e.g. BL(50) is a 50-year block length, and LTT(96) shows long-term trend in data recorded over 96 years.

This showed that the homogeneity over the different regions was moderately acceptable for support of trend from short-term rainfall using result from any other long-term rainfall data at another nearby meteorological station.

- d) Over the period 1940 to 1990, trends in annual rainfall were positive (negative) in the EQR (SEE). The annual rainfall trend in the EQR (SEE) was found to be caused by variations in the OND (JJAS) season.

Acknowledgments

The research was financially supported by an IRO PhD scholarship of KU Leuven. The authors are grateful to the Editor-in-Chief Joseph H.W. Lee as well as the three anonymous reviewers for their constructive comments and suggestions that greatly improved on the quality of this paper.

Appendix. Supplementary material

Supplementary data to this article can be found online at [doi:10.1016/j.jher.2015.09.002](https://doi.org/10.1016/j.jher.2015.09.002).

References

- Abtew, W., Melesse, A.M., Dessalegne, T., 2009. El Niño Southern Oscillation link to the Blue Nile River Basin hydrology. *Hydrol. Process.* 23, 3653–3660.
- Camberlin, P., 2009. Nile Basin climates. In: Dumont, H.J. (Ed.), *The Nile: Origin, Environments, Limnology and Human Use*, vol. 89. *Monographiae Biologicae*. Springer, Dordrecht, pp. 307–333.
- Conway, D., Hulme, M., 1993. Recent fluctuations in precipitation and runoff over the Nile sub-basins and their impact on main Nile discharge. *Clim. Chang.* 25, 127–151.
- Di Baldassarre, G., Elshamy, M., van Griensven, A., Soliman, E., Kigobe, M., Ndomba, P., et al., 2011. Future hydrology and climate in the River Nile basin: a review. *Hydrol. Sci. J.* 56 (2), 199–211.
- Hamed, K.H., 2009. Enhancing the effectiveness of prewhitening in trend analysis of hydrologic data. *J. Hydrol.* 368, 143–155.
- Hulme, M., 1992. Rainfall changes in Africa: 1931–1960 to 1961–1990. *Int. J. Climatol.* 12, 685–699.
- IPCC, 2013. *Climate Change 2013: The Physical Science Basis*. Cambridge University Press, Cambridge, United Kingdom and New York, USA. 1535 pp. Contribution of working group I to the fifth assessment report of the Intergovernmental Panel on Climate Change.
- Kendall, M.G., 1954. Note on bias in the estimation of autocorrelations. *Biometrika* 41, 403–404.
- Kendall, M.G., 1975. *Rank Correlation Methods*, fourth ed. Charles Griffin, London.
- Kibiyi, J., Kivuma, J., Karogo, P., Muturi, J.M., Dulo, S.O., Roushdy, M., et al., 2010. Flood and Drought Forecasting and Early Warning. Nile Basin Capacity Building Networks (NBCBN), Flood Management Research Cluster, Nile Basin Capacity Building Network (NBCBN-SEC) Office, Cairo, Egypt. 68 pp.
- Kizza, M., Rodhe, A., Xu, C.-Y., Ntale, H.K., Halldin, S., 2009. Temporal rainfall variability in the Lake Victoria Basin in East Africa during the twentieth century. *Theor. Appl. Climatol.* 98, 119–135.
- Lyon, B., DeWitt, D.G., 2012. A recent and abrupt decline in the East Africa long rains. *Geophys. Res. Lett.* 39, L02702. doi:10.1029/2011GL050337.
- Mann, H.B., 1945. Nonparametric tests against trend. *Econometrica* 13 (3), 245–259.
- Mphale, K.M., Dash, S.K., Adedoyin, A., Panda, S.K., 2014. Rainfall regime changes and trends in Botswana Kalahari Transect's late summer precipitation. *Theor. Appl. Climatol.* 116, 75–91.
- Nicholson, S.E., 1996. A review of climate dynamics and climate variability in Eastern Africa. In: Johnson, T.C., Odada, E.O. (Eds.), *The Limnology,*

- Climatology and Paleoclimatology of the East African Lakes*. Gordon and Breach, Amsterdam, pp. 25–56.
- Nicholson, S.E., Entekhabi, D., 1986. The quasi-periodic behavior of rainfall variability in Africa and its relationship to Southern Oscillation. *J. Clim. Appl. Meteorol.* 26, 561–578.
- Nyeko-Ogiramoi, P., Willems, P., Ndirane-Katashaya, G., 2013. Trend and variability in observed hydrometeorological extremes in the Lake Victoria basin. *J. Hydrol.* 489, 56–73.
- Onyutha, C., 2015a. Identification of sub-trends from hydro-meteorological series. *Stoch. Environ. Res. Risk Assess.* doi:10.1007/s00477-015-1070-0. in press.
- Onyutha, C., 2015b. Variability of seasonal and annual rainfall in the River Nile riparian countries and possible linkages to ocean-atmosphere interactions. *Hydrol. Res.* doi:10.2166/nh.2015.164. in press.
- Onyutha, C., Willems, P., 2015a. Spatial and temporal variability of rainfall in the Nile Basin. *Hydrol. Earth Syst. Sci.* 19, 2227–2246. doi:10.5194/hess-19-2227-2015.
- Onyutha, C., Willems, P., 2015b. Uncertainty in calibrating generalised Pareto distribution to rainfall extremes in Lake Victoria Basin. *Hydrol. Res.* 46 (3), 356–376. doi:10.2166/nh.2014.052.
- Salas, J.D., Delleur, J.W., Yevjevich, V., Lane, W.L., 1980. *Applied Modelling of Hydrologic Time Series*. Water Resources Publications, Littleton, Colorado, USA. 484 pp.
- Seleshi, Y., Zanke, U., 2004. Recent changes in rainfall and rainy days in Ethiopia. *Int. J. Climatol.* 24, 973–983.
- Sen, P.K., 1968. Estimates of the regression coefficient based on Kendall's tau. *J. Am. Stat. Assoc.* 63, 1379–1389.
- Shiau, J.-T., Huang, W.-H., 2015. Detecting distributional changes of annual rainfall indices in Taiwan using quantile regression. *J. Hydro-Environ. Res.* 9 (3), 368–380.
- Stojković, M., Ilić, A., Prohaska, S., Plavšić, J., 2014. Multi-temporal analysis of mean annual and seasonal stream flow trends, including periodicity and multiple non-linear regression. *Water Resour. Manage.* 28 (12), 4319–4335. doi:10.1007/s11269-014-0753-5.
- Syafrina, A.H., Zalina, M.D., Juneng, L., 2014. Historical trend of hourly extreme rainfall in Peninsular Malaysia. *Theor. Appl. Climatol.* doi:10.1007/s00704-014-1145-8.
- Taye, M.T., Willems, P., 2012. Temporal variability of hydroclimatic extremes in the Blue Nile basin. *Water Resour. Res.* 48, W03513. doi:10.1029/2011WR011466.
- Theil, H., 1950. A rank-invariant method of linear and polynomial regression analysis. *Proc. K. Ned. Akad. Wet. A* 53, 386–392.
- Tierney, J.E., Smerdon, J.E., Anchukaitis, K.J., Seager, R., 2013. Multidecadal variability in East African hydroclimate controlled by the Indian Ocean. *Nature* 493, 389–392.
- van Belle, G., Hughes, J.P., 1984. Nonparametric tests for trend in water quality. *Water Resour. Res.* 20 (1), 127–136.
- van Giersbergen, N.P.A., 2005. On the effect of deterministic terms on the bias in stable AR models. *Econ. Lett.* 89, 75–82.
- von Storch, H., 1995. Misuses of statistical analysis in climate research. In: von Storch, H., Navarra, A. (Eds.), *Analysis of Climate Variability: Applications of Statistical Techniques*. Springer-Verlag, Berlin, Germany, pp. 11–26.
- Wing, H., Cheung, A., Gabriel, B.S., Singh, A., 2008. Trends and spatial distribution of annual and seasonal rainfall in Ethiopia. *Int. J. Climatol.* 28 (13), 1723–1734.
- WMO, 2000. Detecting trend and other changes in hydrological data. In: Kundzewicz, Z.W., Robson, A. (Eds.), *World Climate Program-Water*. WMO/UNESCO, WCDMP-45, WMO/TD-No.1013, Geneva, Switzerland. 157 pp.
- WMO, 2014. Updating baseline climate. Press Release No. 997. <http://www.wmo.int/pages/mediacentre/press_releases/pr_997_en.html> (accessed 05.09.14).
- Yue, S., Pilon, P., Phinney, B., Cavadias, G., 2002a. The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrol. Process.* 16, 1807–1829.
- Yue, S., Pilon, P., Cavadias, G., 2002b. Power of the Mann-Kendall and Spearman's rho tests for detecting monotonic trends in hydrological series. *J. Hydrol.* 259, 254–271.