Journal of Hydrology 489 (2013) 56–73

Contents lists available at SciVerse ScienceDirect

Journal of Hydrology

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

Trend and variability in observed hydrometeorological extremes in the Lake Victoria basin

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ARTICLE INFO

Article history:
Received 14 September 2011
Received in revised form 18 February 2013
Accepted 22 February 2013
Available online 13 March 2013
This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Efrat Morin, Associate Editor

Keywords:
Climate indices
Climate variability
Hydrometeorological extremes
Lake Victoria
Perturbation
Trend

SUMMARY

In the Lake Victoria basin hydrology, trend analysis has mainly been limited to the mean of the hydrological variable without explicit consideration of extremes, which are very crucial in understanding the behaviour of disastrous hydrometeorological events. Since the effects of climate change are unleashed, more through the occurrence of extremes, analysis of both monotonic and cyclic trends in hydrological extremes is very crucial. The presence of a significant linear trend, in a long-term hydrometeorological record of extremes, may provide evidence of a shift from the natural trend to that which is enhanced by, for example, anthropogenic forcing. In addition, cyclic trends analysis of hydrological extremes provides information on the cyclic behaviour of the extreme anomalies that have occurred over and above the natural climate variability and may link them to past consequences and their drivers. Analysis of long term records of extremes for rainfall, temperature and streamflows for selected stations in the Lake Victoria basin, were carried out based on a linear trend test, to detect significant monotonic trends, and quantile perturbation analysis, to detect significant temporal extreme anomalies. In addition, correlations between change in rainfall extremes and that for the other extremes, as well as sunspot maxima, were investigated. The findings indicated that extremes in the Lake Victoria basin are, generally, experiencing positive linear trends. Albeit positive trend was generally demonstrated, the presence of significant linear trend was manifested in the extremes of the data obtained from the stations located in the northern and eastern parts of the Lake Victoria basin. This may suggest that the monotony in the positive trend is a result of an ever increasing and consistent external enhancement of the natural climate agitation. The latter has implications for flood risks if the trend persists in the near future. The cyclic analysis of the behaviour of extremes indicated that the 1940s and the 1970s experienced significantly low extremes. Furthermore, the higher significant anomalies for the 1990s, compared to that for the 1960s, may suggest a more intense enhancement of the change in the natural variability in the recent climate. Correlation between change in the extremes for rainfall and that of the minimum daily temperature was demonstrated to be stronger (c.f. maximum temperature and sunspot maxima) implying that if such correlation persists in the future then change in the extremes of daily minimum temperature can be used as an indicator for the change in rainfall extremes. The investigation of the correlations between climate indices/solar activity and hydrometeorological extremes suggests that oceanic and solar influences are part of the explanation of the variability observed in rainfall and temperatures extremes in the Lake Victoria basin.

1. Introduction

Lake Victoria (locally known as Lake Nalubale) basin has experienced, in the past few decades, recurrent hydrometeorological extreme conditions such as floods and droughts. For example, the impacts of the 1961 extreme event on East African lake levels are well documented: extensive flooding occurred in the region, loss of homes and lives, damage to crops, and emergency food had to be flown into marooned villages (Conway, 2004). During the last few months of 1997, widespread heavy rainfall caused flooding across the East and the Horn of Africa and the levels of many lakes in East Africa rose significantly in response to the heavy rainfall event (Conway, 2004). There was a devastating drought in the early 1980s in most parts of the basin that consequently affected the River Nile flow at the outlet of the basin although the Lake level remained well above that before 1961. Recent extreme events in the basin occurred in the period 2005–2006 in which the Lake level

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http://dx.doi.org/10.1016/j.jhydrol.2013.02.039

dropped significantly and caused shortages in hydro-electricity production (Riebeek, 2006). The trends and the drivers of these hydrometeorological extremes is debated in many studies (Becker et al., 2010; Kizza et al., 2009; Awange et al., 2008a; Conway, 2004) but the debate on the relationships between extreme anomalies is largely lacking. Climate variability triggered by large scale atmospheric circulations and/or by anthropogenic activities could be a major influencing factor in the recurrence of extreme conditions in the Lake Victoria basin. The issue on climate variability and climate change relies heavily on the detection of trends in instrumental records of hydroclimatic variables such as air temperature, precipitation and streamflow.

Looking at the past climate provides insight into how climate responds to both internal and external forcings. The current and recent warming pattern is of particular significance because most of it is very likely human-induced and proceeding at a rate that is unprecedented in the past decades (e.g. Santer et al., 1996, 2003; Hegerl et al., 2006; Ramaswamy et al., 2006). Recent conditions of climate can be unearthed by investigating changes that have occurred over the past. Records of hydrometeorological variables are very crucial in understanding and detecting changes that have occurred over the past. Changes in the observed hydrometeorological variables can be done through investigation to establish the important features of the recent and past climate. Such investigation is the process of demonstrating that the changes have occurred in some defined statistical sense, and may also lead to provision of the reason for the observed changes. In most cases detecting changes in observed hydrometeorological data is done through statistical analysis of the relevant time series. A change in the times series may occur abruptly (step change) or gradually (trend) or may take a cyclic form (cycle) or a combination of trend and cycle with intermittent step jump (Shahin et al., 1993). Such change may affect the overall statistical properties of the time series such as the mean, median, variance or any other aspects of the time series. Understanding changes in time series is very crucial for general water resources planning and other practical applications such as adaptive engineering designs and may, also, situate the aspect of the near future climate into context. Trend exists in a time series data set if there is a significant correlation between the observations and time. Through statistical analysis, quantitative assessments of the time series can identify different patterns of change. For instance, several studies (e.g. Alexander et al., 2006; Chen et al., 2007; Pugacheva et al., 2003; Hipel and McLeod, 1994; López-Moreno et al., 2007; Machiwal and Jha, 2008; Pujol et al., 2007; Sneyers, 1990; Yazdani et al., 2011) have applied trend tests to detect significant changes in precipitation and streamflows.

In addition to linear trend, one other crucial form of change in a time series is the periodicity or cycle. A number of studies (e.g. Blanckaert and Willems, 2006; de Jongh et al., 2006; Machiwal and Jha, 2008; de Jong et al., 2011) have applied either spectral or harmonic analysis to detect periodicity in time series. Meanwhile, Ntegeka and Willems (2008) applied empirical quantile analysis to detect periodicity in long-term rainfall data for Uccle station, Belgium. The main conclusion by Ntegeka and Willems (2008) was that the periodic high extremes temporal clustering highlights the difficulty of attributing "change" in climate series to anthropogenically induced global warming. The study also highlights advantages of quantile perturbation analysis in unearthing very important features of significant change that occur overtime in the hydrological time series.

Previous studies show that trend analysis for rainfall and streamflows extremes in the Lake Victoria basin have not been examined extensively. In addition, attempts to analyse cyclic patterns of hydrological extremes in the Lake Victoria basin by King'uyu et al. (1999) and Awange et al. (2008b) were based on temperature and monthly mean variable (rainfall, water level and discharge), respectively. Most studies aimed mainly at trends in the mean of the variable temporal variability (e.g. Becker et al., 2010; Kizza et al., 2009; Nyenzi, 1990; Ogallo, 1989). Kizza et al. (2009) examined trends in mean annual and seasonal rainfall using MK for several stations in the Lake Victoria basin. They derived most of the precipitation data from monthly values. The results showed that positive trend in the annual rainfall predominate. The study further concludes that the 1960s represent a significant upward jump in the basin rainfall and that, on the seasonal rainfall, the short rains tend to have more trends than the long rains. A study by Ogallo (1979) showed that most of the annual rainfall series in the region were, mainly, of an oscillatory characteristic with no significant trend. Ogallo (1989) used monthly records from over 90 stations in East Africa to study the dominant spatial and temporal modes of seasonal variation using rotated principal component analysis for the period 1922–1983. In particular, he showed that the Lake Victoria region has a distinctive rainfall regime in East Africa as a whole. Such kinds of study, though, have long not been updated. Most studies of trends on the hydrometeorological time series for the Lake Victoria basin had focused mainly on the mean annual or seasonal rainfall amount only and not much attention was paid to extremes, which are antecedents of disastrous events (floods, droughts, etc.). Change in climate is mainly manifested in extreme meteorological events.

Attempt by Conway (2004) to explain climate variability over the East African region showed strong positive correlations between the Southern Oscillation Index (SOI) and annual rainfall totals estimated as basin-wide rainfall. The study however could not explain whether SOI has some influence on the occurrence of rainfall extremes in the basin. Taye and Willems (2012) assessed the influence of climate indices on hydroclimatic extremes over River Blue Nile basin and showed that changes in the Pacific and Atlantic oceans are identified as the major natural causes for the observed (multi)decadal oscillations on the extremes which was a good step towards linking extremes with changes in the oceans. This study made use of a combination of monotonic (linear) and cyclic trends analysis to try to understand the long term trends and variability of hydrometeorological extremes in the Lake Victoria basin. The methods of Mann Kendall (MK) test for linear trend, and quantile perturbation, for cyclic trend analysis, are here employed to investigate linear and cyclic trends in the extremes for daily rainfall, streamflows, maximum temperature (T_{max}), minimum temperature (T_{min}) for selected monitoring stations in the Lake Victoria basin. Assessing trends in precipitation and temperature concurrently allows statements to be made about the drivers of some of these trends, given the fact that the occurrence of rainfall resonate well with changes in temperature across much of the region. Investigations were also made to establish the correlation between hydroclimatic extremes in the Lake Victoria basin and solar activities as well as climate indices.

2. Study area

The Lake Victoria basin is the largest fresh water body in Africa and the second largest in the world. The lake water-body is transboundary in nature characterized by Kenya, Uganda and Tanzania, with Rwanda and Burundi as key sources of the famous River Kagera, as the major contributor to the lake and the remote source of the River Nile. Lake Victoria is, on average, 68,800 km^2, and is geopolitically shared as follows: Kenya (6%), Uganda (43%) and Tanzania (51%) (Awange and Ong'ang'a, 2006). The basin area in Uganda is 59,858 km^2 out of about 197,000 km^2. Lake Victoria stretches, approximately, 415 km from north to south; between latitudes 0°30′N and 3°12′S, and, approximately, 355 km from west to east between longitudes 31°37′ and 34°53′E (Awange and Ong'ang'a, 2006; Nyeko-Ogiramoi et al., 2010). It is situated at an altitude of about 1130 m a.s.l., and has an estimated volume of about 2750 km^2, and an average and maximum depth of 40 m and 80 m, respectively. The climate of the Lake Victoria basin is generally tropical humid, with temperatures ranging from 15 °C, in the highlands, to 28 °C, in the semi-arid areas (Awange and Ong'ang'a, 2006). The mean annual rainfall varies from a minimum of about 886 mm to 2600 mm; the mean evaporative rate over the Lake is in the range 1100–2040 mm, which decreases with increasing altitude, but in some months exceeds rainfall (Nyeko-Ogiramoi et al., 2010). The major rivers draining into, and forming up part of, the Lake Victoria basin, based on geopolitical sources, are Mara, Kagera, Grumeti, Issanga, Mirongo, Mbalageti and Simiyu (Tanzania). The major rivers from the Kenya side are Nzoia, Yala, Nyando, Kibos, Sondu, Mawa, Migori, Kuja, Riaria and Miriu. From Uganda side the rivers are Katonga, Bukora and Ruizi. Kagera, being the single largest river flowing into the lake and shared by Uganda, Rwanda, Burundi and Tanzania, contributes about 33% inflows into the Lake Victoria. Rivers entering the Lake Victoria from Kenya side, which contains smallest portion of the Lake, contribute over 37% of its surface water inflows. About 86% of the total water input, however, is a contribution from precipitation, with evaporative losses accounting for, approximately, 80% of water leaving the lake. The Victoria Nile is the only surface outlet draining the Lake Victoria, with an average outflow of about 23.4 km^3 year^{-1}.

3. Data and methods

3.1. The data

Despite the fact that the Lake Victoria basin contributes the largest volume to the upper River Nile, it has limited hydroclimatic data that hinders detailed hydrometeorological study of the basin. The Lake Victoria basin however has several rainfall stations but few are, currently being operated and maintained (Nyeko-Ogiramoi et al., 2008). River flow and other hydrometeorological data are limited due to the remoteness of many of the catchments, the lack of economic resources and infrastructure to build and maintain monitoring and meteorological sites (Nyeko-Ogiramoi et al., 2010). Station-based data were obtained mainly from the

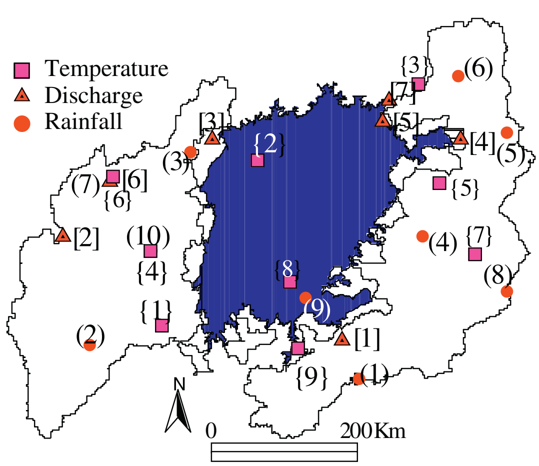

Fig. 1. Hydrometeorological stations for streamflow, rainfall and temperatures in the Lake Victoria basin selected for the study. The data stations shown are those with at least 30 years of records.

River Nile basin Flow Regimes from International, Experimental and Network Data (FRIEND/Nile) project. FRIEND/Nile is a research project of the Nile basin riparian countries. Data with longer records from representative stations in the Lake Victoria basin (Fig. 1) were, carefully selected based on quality and the objective of the study. Of the available data, ten (10), nine (9) and seven (7) stations for rainfall, temperature and streamflows, respectively, spatially distributed over the study area (Fig. 1), were considered for the this study. The selection of the stations was, mainly based on quality criteria, which included, but are not limited to, availability, record length, percentage of missing records, spatial representation and homogeneity of the data. Quality checks were carried out on the data using graphical and statistical methods to ensure that only data with the required quality were employed. The correlation, double mass curve, hydrographs and visual inspections were the methods used to check the quality. The details of data quality assessment are comprehensively given in World Meteorological Organisation (WMO) guide to hydrological practices (1994). Several categories of extreme indices can be extracted from climatic variables. Details of such categories of indices can be found in Alexander et al. (2006). This study considered absolute indices for daily rainfall, streamflows, $T_{\max}$ and $T_{\min}$ values. In the case of rainfall, which varies so much over the Lake Victoria basin compared to temperature, the Areal Reduction Factor (ARF) for the basin (Fiddes et al., 1974) was applied to each of the selected point rainfall series in order to make meaningful comparison which spatial data such as climate indices. The ARF converts the point rainfall data to spatial values. For trend test, using MK methods, annual maximum (AM) daily rainfall, annual Max daily $T_{\max}$, annual Min daily $T_{\min}$ and AM daily streamflow values were extracted. For the analysis of trend using empirical quantile method, flexibility exists in the use of the number of extreme events required per year. That is, optional selection of extreme absolute indices above a given threshold (Ntegeka and Willems, 2008) is possible if the available data is of a resolution of daily or higher. The optional selection of the extreme absolute indices is related to the Peak-Over-Threshold (POT) approach (Willems et al., 2007) which assumed total statistical independency and allows for more absolute values of the extremes in a year to be used in the cyclic trend analysis. Three values of absolute indices per year or POT were used for the analysis of cyclic trend.

Among the climate indices that have been used to explain anomalous rainfall over the East African region, four indices were selected for this study and the data analyzed covered the period 1930–2008. These indices represent influences from three oceans: Pacific, Indian, and Atlantic. The indices are as follow: (1) the Pacific Decadal Oscillation (PDO), the index is calculated by spatially averaging the monthly sea surface temperature (SST) of the Pacific Ocean north of 20_N (Mantua, 2001). The data were obtained from the database of the Joint Institute for the Study of the Atmosphere and Ocean (http://jisao.washington.edu/pdo/PDO.latest). (2) The Southern Oscillation Index (SOI); the data were obtained from the Climate Research Unit database (http://www.cru.uea.ac.uk/cru/data/soi/). This data set is calculated on the basis of the method given by Ropelewski and Jones (1987). The SOI is defined as the normalized atmospheric pressure difference between Tahiti and Darwin. (3) The Indian Ocean Dipole (IOD) is defined as the difference between the sea surface temperatures (SST) in the western (50 E–70 E and 10 S–10 N) and eastern (90 E–110 E and 10 S–0 S) equatorial Indian Ocean. IOD data were obtained from the Japan Agency for Marine-Earth Science and Technology (http://www.jamstec.go.jp/frsgc/research/d1/iod/). (4) The Atlantic Multidecadal Oscillation (AMO); the index is defined as the SST averaged over 0–60 N, 0–80 W minus SST averaged over 60 S–60 N (van Oldenborgh et al., 2009). The data were obtained from http://climexp.knmi.nl/data/iamo_hadsst2.dat.

3.2. Linear trend

In hydrological time series, linear trend, for example, is, normally, introduced through natural or artificial changes. The focal tenet of linear trend analysis is to detect shifts (in decreasing or increasing direction) in hydrometeorological time series and to describe possible generating processes underlying a given sequence of observations. The most sustained, non-parametric traditional methods, among others, for detecting linear trends in time series are the Man-Kendal (MK) (Mann, 1945; Kendall, 1975) and Spearman's rho (SR) (Maritz, 1981) test methods. These methods have, long, been applied to many hydrological and climatological situations (e.g. Kundzewicz, 2004; Yue and Wang, 2004a,b; Alexander et al., 2006; Yue et al., 2002a) where readers can find more details. The MK method for trend testing is a non-parametric (distribution free) approach. That is, the method does not require any assumption about the form of distribution the data is derives from. However, the prerequisite of the test is that the data are drawn from independent identically distributed (iid) random variable. The main benefit of the non-parametric statistical tests, compared to parametric statistical tests, is that the data need not conform to any particular distribution and are thought to be more suitable for non-normally distributed data and censored data, which are frequently encountered in extremes of hydrometeorological time series. Yue et al. (2002a) have rigorously, examined the powers of the MK and the SR tests for detecting linear trends in time series. The study demonstrated that the power of the tests is an increasing function of the slope of trend, sample size, and pre-assigned significance level. They further stated that there is little basis for choosing either MK in preference to SR test or vice versa because both tests provide identical results in the absence of autocorrelation. The details of the procedure for trends test using the MK are described in a number of literatures (e.g. Alexander et al., 2006; Yue et al., 2002a). The null hypothesis, H_0, is that there is no trend in the data and the trend test statistic, S, is evaluated for significance based on bootstrapping resampling technique. The bootstrapping helps to circumvent the need for stern adherence of the data to the test assumptions and example can be found in Kundzewicz (2004). For the extreme time series which violate the assumption of a no serial correlation, the method proposed by Yue and Wang (2004a,b) was applied. Yue et al. (2002b) demonstrated that the existence of serial correlation alters the variance of the estimate of the MK statistic, S. Yue and Wang (2004a,b) proposed a method in which the variance of S is modified by the use of an effective sample size, n^*, which is also a function of the actual sample size, n. An effective sample size is the 'effective' number of independent observations in an autocorrelated time series. Zhang and Zwiers (2004) however attempted to invalidate the method proposed by Yue and Wang (2004a) to eliminate the effect of serial correlation in a time series, but the reply by Yue and Wang (2004b) to Zhang and Zwiers (2004) indicated that the critism by Zhang and Zwiers (2004) were actually groundless and was were misconceptions. More details on how to deal with autocorrelated time series using the 'effective' sample size based method can be found in Yue and Wang (2004a,b).

3.3. Cyclic trend

Periodicities (cyclic trends) in natural time series are, usually, due to the astronomical cycles such as the earth's rotation around the sun or any other cyclic climatic phenomenon such as the ENSO (El Niño/La Niña-Southern Oscillation). The most obvious example of a cyclic trend is the seasonality. The most recent and robust method for analysing cyclic trend (QPMtc) in hydrometeorological data is the quantile perturbation and has been used to investigate the historic changes in ranked extremes (Ntegeka and Willems, 2008). This approach is very robust because it amalgamates aspects of frequency, practiced in extreme value analysis, and perturbation; used in climate change impact studies. The technique is analogous to the frequency-perturbation approach applied as one of the methods for deriving climate change scenarios from historical series using information from climate models runs (Willems and Vrac, 2011; Mpelasoka and Chiew, 2009). For climate change impacts analysis, instead of applying one factor to the whole range of values and all the time scales, different factors can be derived based on the ranked values. The change factors (perturbations) are ratios or differences of two similarly ranked values obtained from the future (climate model scenarios) and the observed time series. The quintessence of QPMtc, however, is solely based on historical time series and given the fact that perturbation is a relative change, it necessitates two series. For the climate-model based approach, one of the series is taken as the reference or baseline series while the other is a future scenario series. In the QPMtc, one of the series is the long-term historical time series (baseline series/reference series) while the other series is taken from a particular block (subseries) of interest or where the change is being investigated. Given a particular block of series of B_L-years, one of the series contains the actual extremes within the block while the other series is derived from the distribution of the original long-term historical time series to obtain a reference series. The extreme values within each block are ranked in order to relate them to return periods of B_L/i, where i is the rank of each extreme value. The ranking ensures that the extreme values correspond to the quantiles $q(B_L)$, $q(B_L/2),\ldots,q(B_L/i)$, where $q(B_L/i)$ is the quantile corresponding to return period of B_L/i years. If N_L is the total record length of the extreme time series under consideration, similarly, $Q(N_L)$, $Q(N_L/2),\ldots,Q(N_L/i)$ are the quantiles corresponding to $N_L, N_L/2,\ldots,N_L/i$ years return periods, respectively. It can be noticed that the return periods $B_L, B_L/2,\ldots$, do not, obligatorily, coincide with the empirical return periods of $N_L, QN_L/2,\ldots$, years and in such cases, the $Q(N_L/i)$ values are obtained by linearly interpolating from the boundary values in the extreme series before $q(B_L/i)$ is compared with the interpolated value, $Q(N_L/i)$. The details of this method has been fully discussed in Ntegeka and Willems (2008) and further applications of the method can be found in Taye and Willems (2012) and Mora and Willems (2011).

3.3.1. Application to quantitative time series

Changes that occur in quantitative hydrometeorological variables such as rainfall, evapotranspiration and streamflows can be compared in terms of ratios. For example, changes in the extremes in the quantitative time series can be derived as ratios of the quantiles with similar return periods in the sub-series (the block series) and the reference/baseline series (full series). Using the same notation provided in Section 3.3 the ratios can be represented as $q(B_L)/Q(N_L)$, $q(B_L/2)/Q(N_L/2),\ldots,q(B_L/i)/Q(N_L/i)$. Fig. 2a illustrates the estimation of the first three values in the reference series for an example rainfall dataset of the daily rainfall extremes intensities of station (7) for $B_L = 10$ years. The curve contains all the selected extremes in the dataset for a full period of 87 years. Using linear interpolation, estimates of the quantiles from the reference series with similar return periods as those in the block series or a particular given block series can be obtained. Based on a sliding window of one step, a similar procedure is followed for all the other sets of blocks of series when estimating the reference series. In each 'window slide', the number of perturbations is equivalent to the block length (size) and cannot exhibit the temporal nature of the changes in the extremes. In order to reveal the temporal variability of the perturbations, an average perturbation value for each block of years is estimated from all the block perturbations centered in the block. Similarly, it is also possible to obtain the average of the reference series, which if multiplied by the average

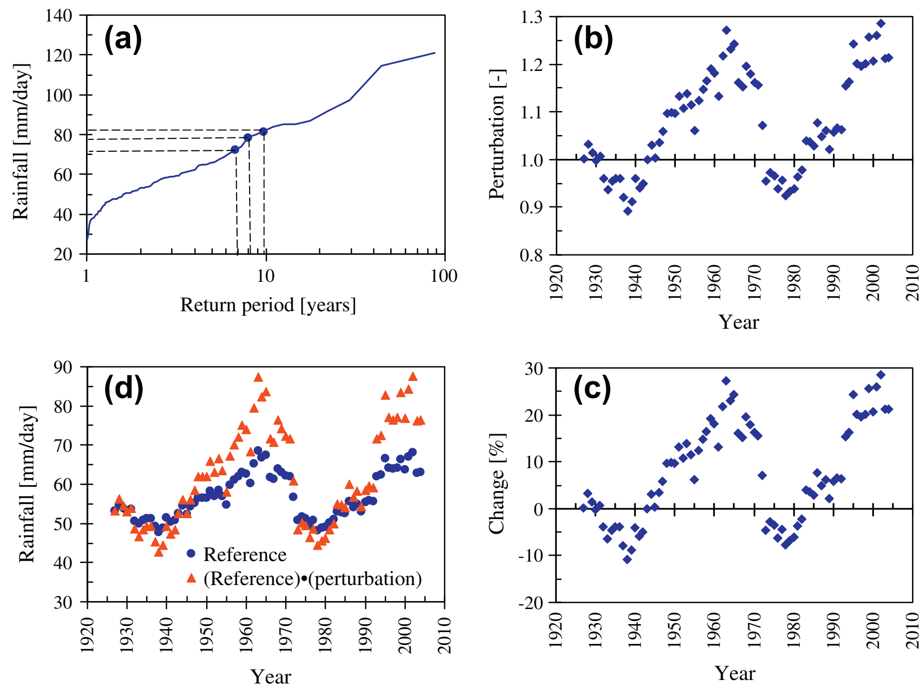

Fig. 2. Rainfall quantiles in reference calculation for an example dataset of rainfall intensities (a), evolution of the estimated changes in the extreme time series: (b) perturbations, (c) percentage change and (d) reference series.

perturbation gives the value of the average of all the extremes for the given block.

These average perturbation factors represent anomalies in quantiles and are derived in this paper for moving block periods or subseries of 10 years length, moved with 1-year step from the beginning, toward the end of the full available series.

Fig. 2b illustrates the temporal evolution of perturbation over time; and the equivalent in percentage change is shown in Fig. 2c. Fig. 2d illustrates the temporal evolution of the mean of the reference and that of the actual extremes series. Given the value of the percentage change, $\%P$, perturbation (P) can be obtain as $1 + (\%P)/100$. The procedure described above was repeated for all the selected rainfall stations in order to analyze changes in rainfall extremes over the study area. Similarly, the same methodology was applied to streamflows extremes for all the selected streamflows stations.

The anomalies of extreme time series can be seen as a series of quantile perturbation above a certain return period. The average quantile perturbation calculation assumes that above a certain exceedance probability, the perturbations are constant. This can be proved by explicitly calculating the slope of the block perturbations and then comparing it with, say bootstrapped 95% confidence interval (Ntegeka, 2011). In the work of Ntegeka and Willems (2008), QPMtc was only applied to quantitative variables such as rainfall, evapotranspiration and streamflow. However, the technique can also be applied to qualitative variable such as temperature in the same way; but requires that temperature are in absolute units.

3.3.2. Significance testing

The temporal evolution of perturbation can reveal whether the most recent changes in climate can be considered statistically significant in contrast with the natural temporal variability. Identification of statistically significant cyclic trends enables an assessment of the likelihood of climate change effects during the previous decades. Confidence intervals are calculated on the perturbation factors, under the null hypothesis of no trend or serial dependence in the occurrence of the extremes in time. This is done to test whether the trends and anomalies identified in the historical series are significant. The confidence intervals are calculated by a nonparametric bootstrapping technique (e.g. Kundzewicz, 2004). The values in the full series are randomly resampled a large number of times (1000 bootstrap runs; each run containing the same number of values as in the full series) without replacement. For each run, perturbation factors are recomputed, where after confidence intervals are calculated for each time step based on the ranked 1000 perturbation factors per time step. Since these confidence intervals define regions of expected variability under the null hypothesis, any anomaly value outside the confidence bounds is considered to be statistically significant (hypothesis of no trend or serial dependence is rejected), while the region inside the confidence bounds is considered insignificant (hypothesis accepted). Based on visual exploration, it is also possible to spot out periods that depict significant deviations under the null hypothesis of no change with respect to the reference series (Fig. 2d).

3.3.3. Sensitivity of block length

The QPMtc is, however, sensitive to block length considered and to capture a meaningful change varying a block length between 5 and 15 years is sufficient to check the persistence of perturbation and hence identification of clustering or systematic changes of the extremes in a given period (Ntegeka, 2011). The choice of the block length may also depend on the objective of the study. In this study, a block length of 10 years was found consistent and used. For more details on the choice and sensitivity of block length, readers are referred to Ntegeka (2011) and Ntegeka and Willems (2008).

3.3.4. Application to temperature data

Application of QPMtc to qualitative climatic variable such as temperature requires a new definition of perturbation. Since perturbation is a relative change, perturbation for temperature can

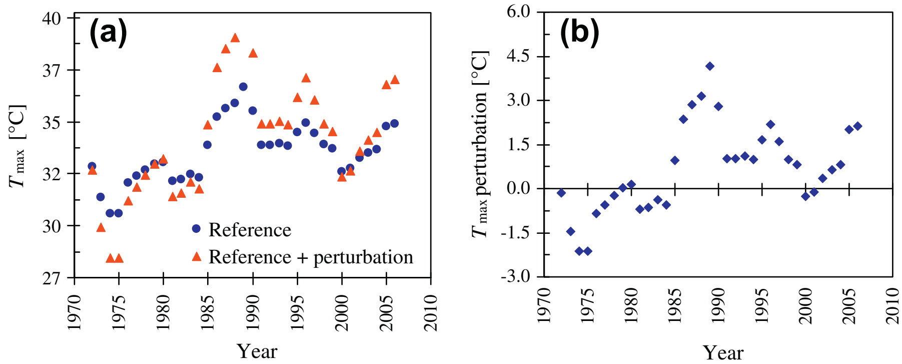

Fig. 3. (a) Temperature changes in reference calculation for an example dataset of maximum temperature and (b) evolution of the estimated maximum temperature perturbation in extreme time series.

be defined as the difference of two temperature values with similar return period obtained from the ranked series of the block series under consideration and the reference series (Fig. 3a) is obtained from the original series. Note that the temperature values need to be in absolute units, Kelvin (K). However, the results can be displayed in degree centigrade (°C). Fig. 3a illustrates the temporal evolution of the mean of the reference and that of the actual temperature extremes series; meanwhile, Fig. 3b illustrates the temporal evolution of temperature perturbation over time.

3.3.5. Comparison of trends in rainfall and temperature extremes

In order to unearth the links between change in rainfall extremes and temperature extremes, perturbations of rainfall and that of temperature (T_{max} and T_{min}) were compared. Given that each of the selected temperature stations does not necessarily come from the respective same locations as that for the selected rainfall stations, the average perturbations were compared. To obtain the average perturbation for rainfall, for example, for a given year, the values of rainfall perturbations for all the selected rainfall stations were considered. The average perturbations, for all the other years, were obtained in a similar way and were done for the periods where most of the stations have data. The topography of the Lake Victoria basin is fairly homogeneous and making the use of average value provides a fairly consolidated result (Nyeko-Ogiramoi, 2011). The average perturbations for T_{max} and T_{min} (temperature) were also calculation in the same way as that of the rainfall. Comparison of the average perturbations was made in two ways. In the first case, the values of the normalized average perturbations for rainfall and temperature were compared in the same chart. Normalization of the average perturbations was done by their respective mean value. In the second case, the correlations between the average perturbations of rainfall and that of corresponding temperature were calculated. To this extent, it was possible to compare the perturbations of rainfall and temperature. The influence of temperature change on rainfall extremes can be determined by considering the average perturbation of rainfall per unit average temperature perturbation. That is, change in rainfall per unit change in temperature. This was done for each year and only for the period where both data are available.

3.3.6. The influence of solar activity on trend of rainfall extremes

Historical record showed that the Lake Victoria levels rose during every peak of about 11-year sunspot (hereafter defined) cycle since the late 19th century (Stager et al., 2005). Sunspots are seen as "small" dark spots on the surface of the sun. They are easy to observe and count if the sunlight is strongly filtered. The collection of sunspot numbers is mainly done by the International Sunspot Count, Brussels. The data are available freely in public domains. While in Stager et al. (2007), it is reported that "peaks in the ~11-year sunspot cycle were accompanied by Victoria level maxima throughout the 20th century, due to the occurrence of positive rainfall anomalies ~1 year before solar maxima". They further argued that if the Sun-rainfall relationship persists in the future, sunspot cycles can be used for long-term prediction of precipitation anomalies and associated outbreaks of insect-borne disease in much of East Africa. This information may need to be corroborated from the rainfall extremes perspective.

An attempt to establish how the changes in sunspot maxima influence the changes in rainfall extremes is, herein, made. Application of QPMtc was applied to sunspot maxima series and the correlation between the perturbation of sunspot maxima and that of the rainfall extremes was established. That is, the average perturbations of rainfall were compared to that of sunspot in a similar way as to that of temperature.

3.3.7. Hydroclimatic correlation with climate indices

The temporal variability in the hydrometeorological extremes and the related impacts has strong implications for water and agricultural management. The questions about the driver(s) that influence such variability and whether predictions can be made on the extremes variability/oscillation based on such drivers remain a big concern. In order to partly address this concern and try to unveil the causes of the variability in the extremes, the QPMtc analysis was performed on the selected climate indices and the correlation coefficients between the rainfall and maximum and minimum temperature anomaly factors and those of the climate indices were obtained. The statistical significance of the correlation was assessed using the *t*-test for 1% and 5% significance levels. The assumption made on this is each nonoverlapping block of series delivers one independent anomaly value, in order to account for the dependency introduced while using the moving average method in the QPMtc analysis. The sample size equals the total number of independent anomaly values of the nonoverlapping blocks. The anomalies were compared by use of graphs while the correlations values and their significance were presented in table.

4. Results and discussion

4.1. Monotonic trend

4.1.1. Rainfall extremes

Table 1 contains results for the MK trend test on the AM daily rainfall (rainfall extremes). Column (1) of Table 1 provides the station identifier, ID, of each of the selected rainfall stations and the numbers embraced after each of the IDs using parentheses, ( ), are the numbers indicated in Fig. 4, which, also, shows the spatial

Table 1
Basic properties and *P*-values of rainfall extremes for 10 selected rainfall stations in the Lake Victoria basin.

Station (ID)	n (years)	n/n^*	Mean (mm/d)	C_V	C_S	C_K	Correlation r_1	Limits Upper	Lower	Slope, b (mm/(per year)d/year)	(11)/(4)	*P*-value P	P^*	*P*-value (R) $P_{\alpha=0.05}$	$P_{\alpha=0.1}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
9333005 (1)	79	1.271	65.3	0.303	1.029	1.936	0.121	0.201	−0.226	0.0198	0.000302	0.572	0.564	0.973	0.954
10149 (2)	64	1.395	69.7	0.558	2.813	10.028	0.168	0.232	−0.267	0.2756	0.003956	0.976	0.952	0.975	0.956
9031026 (3)	57	1.311	67.1	0.331	0.984	0.813	0.137	0.235	−0.276	0.4167	0.006212	0.985	0.972	0.975	0.948
9134008 (4)	79	1.497	61.6	0.298	0.985	1.172	0.201	0.205	−0.230	0.2536	0.004113	0.999	0.996	0.975	0.952
9035127 (5)	45	1.352	61.1	0.444	3.593	16.521	0.153	0.225	−0.270	0.3762	0.006161	0.995	0.988	0.976	0.953
8935076 (6)	45	1.651	57.0	0.267	−0.133	−1.013	0.251	0.275	−0.320	0.5000	0.008769	1.000	0.995	0.980	0.957
9030003 (7)	87	3.365	56.7	0.298	1.452	2.905	0.548	0.191	−0.214	0.1095	0.001932	0.976	0.860	0.978	0.949
9235000 (8)	63	1.394	61.6	0.360	2.005	6.998	0.167	0.215	−0.247	0.2042	0.003313	0.957	0.919	0.973	0.956
9233008 (9)	58	2.505	82.0	0.342	1.193	1.904	0.437	0.234	−0.269	0.0611	0.000745	0.639	0.589	0.978	0.954
9131028 (10)	47	1.386	61.5	0.286	0.608	−0.164	0.165	0.260	−0.302	0.0092	0.000149	0.551	0.543	0.976	0.952

ID: Station identifier; n: actual sample size; n^*: effective sample size; C_V: coefficient of variation; C_S: coefficient of skewness; C_K: coefficient of kurtosis; r_1: lag-1 autocorrelation coefficient and its upper and lower limits of the confidence interval at the significant level of 0.05; b: slope of linear trend; P and P^*: the probability values, *P*-values, of the MK *S*, estimated from the original data, before correcting for lag-1 autocorrelation (P) and after correcting for lag-1 autocorrelation (P^*); *P*-values of the upper quartiles of the replicates of the data corresponding to 95% confident interval, $P_{\alpha=0.05}$, and 90% confident interval, $P_{\alpha=0.05}$.

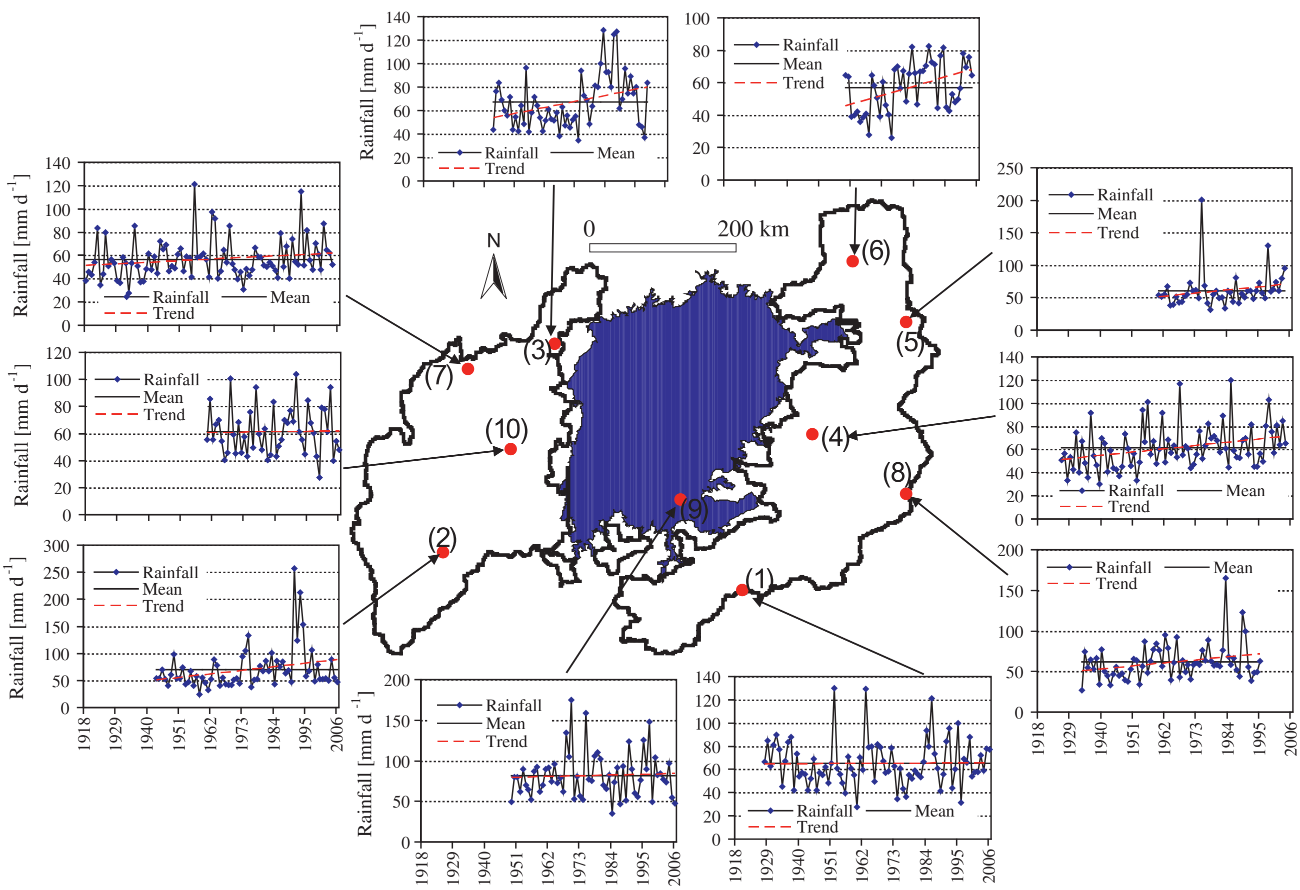

Fig. 4. Time series plots of daily AM rainfall for selected rainfall stations in the Lake Victoria basin.

loci of the selected stations in the study area. The actual record length, n, the ratio between n and effective record length, n^*, n/n^*, the mean, coefficient of variation, C_V, coefficient of skewness, C_S, and coefficient of kurtosis, C_K, of the rainfall extremes, are presented in columns (2)–(7). For normally distributed random time series, its C_S and C_K should be equal to 0 and 3, respectively. It is evident from Table 1 that the rainfall extremes of 9 out of the 10 rainfall stations are positively skewed and in all likelihood poorly described by a normal distribution. The lag-1 serial correlation coefficient, r_1, and its upper and lower limits of the confidence interval at the significant level of 0.05 of the two-tailed test for autocorrelation on the rainfall extremes are presented in columns (8)–(10), respectively. It can be seen that 8 out of the 10 extreme rainfall series are not significantly serially correlated at the significant level of 0.05. Hence, the application of MK trend test to these stations, without considering serial correlation, is valid.

The magnitude of the gradient (slope) of the trend was estimated using the method proposed by Theil (1950) and Sen (1968). The value of the slope is provided in column (11), and is, hereafter, referred to as Sen's slope. Sen's slope is a robust method for estimating slope of linear trend (Yue et al., 2002a). The Sen's slope, *b*, divided by the mean of the extremes is presented in column (12), and is termed a unit slope. Sen's slopes of all the time series are positive, which, is an indication of the likelihood of an increasing trend of the rainfall extremes for the study area. Visual exploration of Fig. 4 also shows that the magnitude of the Sen's slopes, indicated in Table 1, reflects the gradual tendency of the linear trends. The mean cross-correlation of the cross-correlation coefficients (also see Yue and Wang, 2002) among the 10 rainfall stations is 0.0235. This mean cross-correlation value, compared to the mean values of the upper (0.0576) and the lower (0.0001) limits of the 95% confident limits, implies that the cross-correlation among the sites could be ignored. Thus, there is some evidence that the upward trends may not be due to chance alone. In other words, given the available data, the rainfall extremes in the Lake Victoria region, for the past 5–8 decades, have been experiencing an upward trend, irrespective of the significance of the linear trend.

The probability values, *P*-values, of the MK *S*, estimated from the original data, before correcting for lag-1 autocorrelation, *P*, and after correcting for lag-1 autocorrelation, P^*, are indicated in columns (13)–(14) of Table 1. The *P*-values of the upper quartiles of the replicates of the data corresponding to 95% confident interval, $P_{\alpha=0.05}$, and 90% confident interval, $P_{\alpha=0.05}$, are indicated in columns (15)–(16) of Table 1. As already stated, the presence of statistically significant autocorrelation can have an impact on the significance of the linear trend tests (Yue and Wang, 2002; Villarini and Smith, 2010). As reported by Cox and Stuart (1955), "positive serial correlation among the observations would increase the chance of significant answer even in the absence of a trend."

The modification of the MK variance by a correction factor, n/n^*, before evaluating for the significance of trend was, thus, to account for the effect the significant serial correlation on the trend test results, especially for stations (7) and (9). This is because of the high values of r_1 for stations (7) and (9). Comparison of the values of *P* and P^*, in columns (13)–(14), shows that the effect of significant positive autocorrelation can influence the rejection of H_0 and indeed vindicates the need for autocorrelation correction. It can, also, be seen from Table 1 that the rainfall extremes series showed existence of linear trends which are statistically significant at $\alpha = 0.1$, *S*(0.1), for station (8) and *S*(0.05) for stations (2), (3), (4), (5) and (6). Although the Sen's slopes for all the extreme rainfall series considered are positive, the existence of monotonic trends for stations (1), (7), (9) and (10) is not statistically significant at any of the indicated significant levels, NS(0.1, 0.05). Thus, 60% of the extreme rainfall series showed significant positive (increasing) trends. The visual satisfaction of the magnitude of the inclination between the mean-line (continuous line) and the approximate linear trend-line (dash line), indicated in Fig. 4, is an important complement to the test results. Given that there is an apparent nexus between the magnitude of the Sen's unit slope and the significant answer, the Sen's unit slope may provide evidence for significant answer if other influences are negligible.

4.1.2. Extremes of T_{max}

Table 2 provides results for the MK trend test on the AM daily $T_{\max}$ ($T_{\max}$ extremes). The definitions of the notations indicated in each of the columns of Table 2 are similar to the ones provided in Section 4.1.1 for Table 1. The IDs, embraced by parentheses, { }, are the numbers indicated in Fig. 5, which also indicate the spatial loci of the selected temperature stations in the study area. It is evident from Table 2 that all the $T_{\max}$ extremes series are positively skewed and in all likelihood poorly described by a normal distribution. Table 2 shows that 8 out of the 9 $T_{\max}$ extreme series sets are *S*(0.05). Irrespective of the level of the significance of the autocorrelation, useful trend test results, however, were obtained after correcting for the possible effect of autocorrelation. Column (11)–(12) of Table 2 provides the values of the Sen's slope, and the unit slope. The magnitude of the slope for station {7} is naught, which is an indication that there is no linear trend at all in the available data for station {7} and this may be attributed to stationary climate in that period of records. Stations {3}, {5} and {6} have negative slopes and stations {1}, {2}, {4}, {8} and {9} showed evidence of positive slopes. Visual analysis of Fig. 5 also reflects the gradual tendency revealed by the Sen's slopes.

The mean cross-correlation of the cross-correlation coefficients among the 9 $T_{\max}$ stations is 0.0251. The corresponding mean values of the upper and the lower limits of the 95% confident limits are 0.1160 and 0.00013, respectively. This evidence implies that the cross-correlation among the sites could be neglected. Thus, the evidence of increasing and decreasing linear trend may not be due to chance alone for that station but also because of the fact that the climate might have been changing. Visual analysis of Fig. 5 also shows that the $T_{\max}$ extreme series for stations {5} and {6} have tendencies of decreasing trends. A more critical visual inspection of chart for stations {1}, {4}, {6} and {9} in Fig. 5 reveals that, albeit the approximate linear trend-line indicates an increasing

Table 2
Basic properties and *P*-values of $T_{\max}$ extremes for nine selected temperature stations in the Lake Victoria basin.

Station (ID)	*n* (years)	n/n^*	Mean (°C)	C_V	C_S	C_K	Correlation		Slope, *b*			*P*-value		*P*-value (R)	
							r_1	Limits Upper	(°C/(per year)year) Lower		(11)/(4)	*P*	P^*	$P_{\alpha=0.05}$	$P_{\alpha=0.1}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
9231011 {1}	33	2.3	31.5	0.077	1.503	1.671	0.405	0.286	−0.347	0.1000	0.0032	0.999	0.979	0.975	0.948
9032010 {2}	36	19.0	32.3	0.067	0.669	3.041	0.937	0.269	−0.325	0.0706	0.0022	0.997	0.736	0.973	0.946
8934140 {3}	31	5.0	34.4	0.050	0.898	1.453	0.692	0.278	−0.343	−0.1000	−0.0029	0.000	0.047	0.973	0.947
9232027 {4}	32	3.9	29.5	0.053	0.086	0.635	0.613	0.313	−0.375	0.0526	0.0018	0.968	0.825	0.971	0.946
60462 {5}	34	1.2	33.7	0.063	1.174	1.274	0.096	0.301	−0.360	−0.0160	−0.0005	0.334	0.348	0.978	0.956
9030000 {6}	30	1.9	30.2	0.055	1.009	1.175	0.333	0.293	−0.359	−0.0414	−0.0014	0.255	0.318	0.969	0.946
6070 {7}	39	27.8	32.9	0.056	2.553	8.142	0.972	0.244	−0.295	0.0000	0.0000	0.558	0.511	0.971	0.945
9132002 {8}	39	28.8	33.4	0.074	0.797	0.236	0.975	0.278	−0.329	0.0913	0.0027	0.996	0.690	0.971	0.944
9233044 {9}	37	28.3	35.0	0.044	1.514	3.061	0.977	0.276	−0.330	0.0625	0.0018	1.000	0.747	0.977	0.949

ID: Station identifier; *n*: actual sample size; n^*: effective sample size; C_V: coefficient of variation; C_S: coefficient of skewness; C_K: coefficient of kurtosis; r_1: lag-1 autocorrelation coefficient and its upper and lower limits of the confidence interval at the significant level of 0.05; *b*: slope of linear trend; *P* and P^*: the probability values, *P*-values, of the MK *S*, estimated from the original data, before correcting for lag-1 autocorrelation (*P*) and after correcting for lag-1 autocorrelation (P^*); *P*-values of the upper quartiles of the replicates of the data corresponding to 95% confident interval, $P_{\alpha=0.05}$, and 90% confident interval, $P_{\alpha=0.05}$.

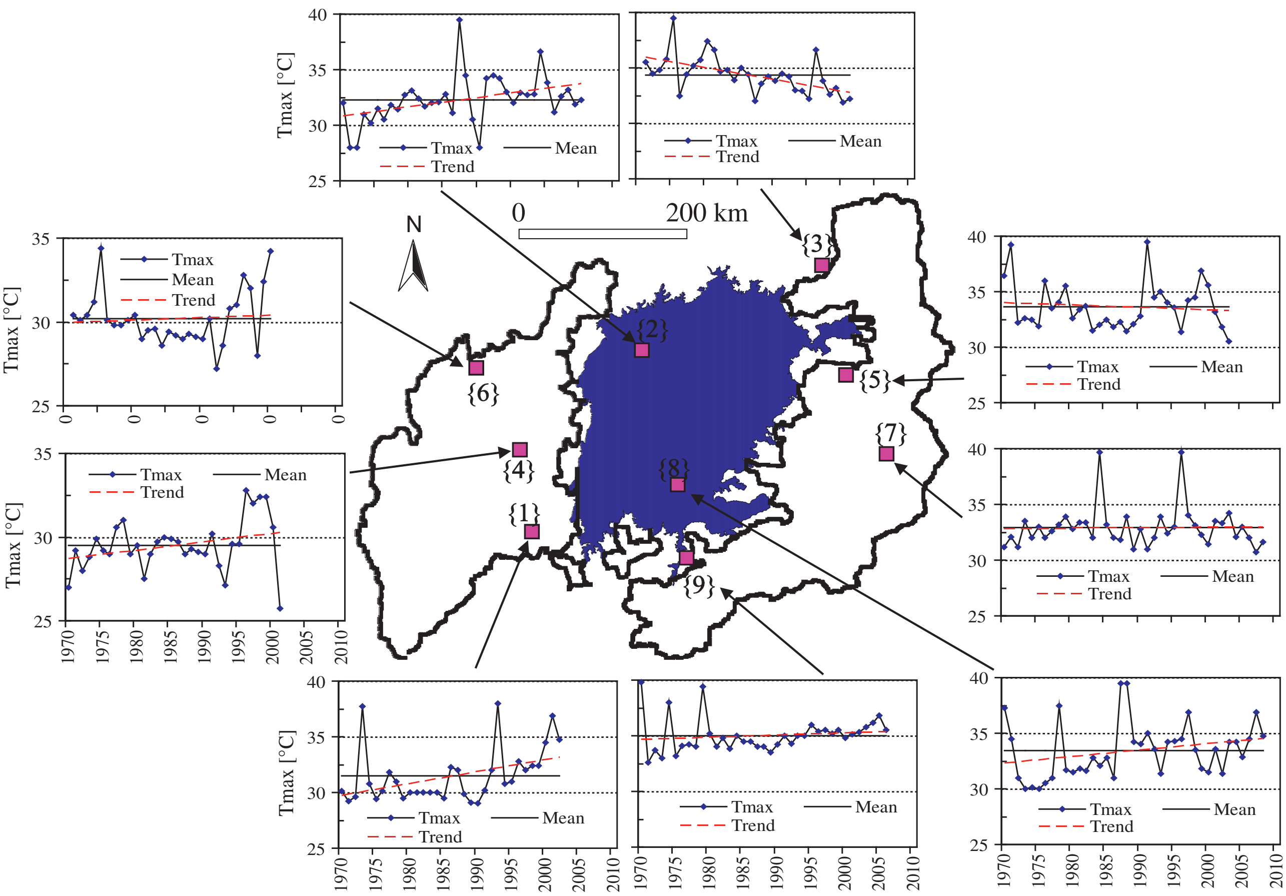

Fig. 5. Time series plots of the AM of T_{max} for selected temperature stations in the Lake Victoria basin.

Table 3
Basic properties and *P*-values of T_{min} extremes for nine selected temperature stations in the Lake Victoria basin.

Station (ID)	*n* (years)	n/n^*	Mean (°C)	C_V	C_S	C_K	Correlation			Slope, *b*		*P*-value		*P*-value (R)	
							r_1	Limits		(°C/(per year)year)		*P*	P^*	$P_{\alpha=0.05}$	$P_{\alpha=0.1}$
								Upper	Lower		(11)/(4)				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
9231011 {1}	31	2.3	13.0	0.105	−0.254	0.054	0.405	0.306	−0.371	0.05240	0.00403	0.947	0.857	0.970	0.947
9032010 {2}	23	1.7	12.7	0.109	0.367	0.470	0.272	0.337	−0.424	0.00000	0.00000	0.604	0.580	0.962	0.940
8934140 {3}	30	4.9	12.0	0.143	0.191	2.871	0.683	0.291	−0.357	0.11436	0.00954	1.000	0.964	0.976	0.950
9232027 {4}	31	2.8	12.4	0.092	−0.012	0.511	0.488	0.305	−0.369	0.04473	0.00361	0.992	0.924	0.970	0.937
60462 {5}	37	27.7	12.8	0.119	0.416	−0.041	0.975	0.299	−0.353	0.00769	0.00060	0.672	0.534	0.977	0.950
9030000 {6}	31	2.7	12.4	0.089	−0.853	−0.150	0.482	0.322	−0.386	0.00000	0.00000	0.373	0.423	0.974	0.949
6070 {7}	35	14.5	10.1	0.177	−0.716	−0.461	0.905	0.287	−0.344	0.13280	0.01321	1.000	0.902	0.974	0.947
9132002 {8}	32	2.1	14.0	0.113	−0.693	1.226	0.376	0.290	−0.352	0.06667	0.00476	0.996	0.967	0.974	0.948
9233044 {9}	35	21.9	12.5	0.098	0.148	−0.193	0.955	0.295	−0.352	0.06594	0.00529	0.995	0.711	0.971	0.937

ID: Station identifier; *n*: actual sample size; n^*: effective sample size; C_V: coefficient of variation; C_S: coefficient of skewness; C_K: coefficient of kurtosis; r_1: lag-1 autocorrelation coefficient and its upper and lower limits of the confidence interval at the significant level of 0.05; *b*: slope of linear trend; *P* and P^*: the probability values, *P*-values, of the MK *S*, estimated from the original data, before correcting for lag-1 autocorrelation (*P*) and after correcting for lag-1 autocorrelation (P^*); *P*-values of the upper quartiles of the replicates of the data corresponding to 95% confident interval, $P_{\alpha=0.05}$, and 90% confident interval, $P_{\alpha=0.05}$.

trend, the path of a decreasing trend appears to have been abruptly altered by the T_{max} extremes experienced in the recent decade (1990s).

It can be seen from Fig. 5 that the T_{max} extremes series showed existence of linear trends, which are, *S*(0.1), for station {1} only. The linear trends identified in T_{max} extremes series for all other stations are not statistically significant at any of the indicated significant levels. Although the Sen's slopes for 5 out 9 T_{max}, and 3 out of 9 extremes series are positive and negative, respectively, the existence of monotonic trend for only one station, {1}, is *S*(0.05). Thus, only about 10% of the extreme T_{max} series selected showed significant increasing linear trends.

4.1.3. Extremes of T_{min}

Table 3 provides results for the MK trend test on the annual minimum daily T_{min} (T_{min} extremes). The notations indicated in each of the columns were defined in Section 4.1.1. The IDs for the T_{min} stations are similar to that of T_{max}. It can be seen that the values of C_V for T_{min} extremes are much higher than the corresponding values for T_{max} extremes. This is an indication that the amplitude of the variation of T_{min} extremes are higher than those of T_{max} extremes. It is also evident from Table 3 that T_{min} extreme series of 4 and 5 stations are positively and negatively skewed, respectively. All of the T_{min} extremes series are also poorly described by a normal distribution. The magnitudes of the slope for stations {2} and {6} are naught, which is an indication that there is no linear trend in the available data. All other stations showed evidence of positive slopes. Visual inspection of Fig. 6 also reflects the gradual tendency revealed by the Sen's slopes indicated in Table 3. The mean cross-correlation of the cross-correlation coefficients among the 9 T_{min} stations is 0.0253. The corresponding mean values of the upper and the lower limits of the 95% confident limits are 0.1255 and 0.00014, respectively. The low values of the correlation among the stations show that the cross-correlation among the sites could be neglected. Thus, the evidence of increasing linear trend, demonstrated by all the T_{min} extremes, may not be due to chance alone. Visual inspection of Fig. 6 shows that the strong increase in the T_{min} extremes in the 1990s is demonstrated by all the T_{min} stations, except for station {6}. It can, further, be seen from Table 3 that the existence of linear trend in the T_{min} extremes for stations {3} and {8} are $S(0.1)$. However, visual inspection of Fig. 6 gives the impression that station {7} has steeper linear trend than that for station {3} and {8}. Indeed, the Sen's slope for {7} is greater than that of {3} and {8}. Thus, insignificant trend in T_{min} extremes for station {7} can only be explained by the value of its r_1, which is much higher than that of {3} and {8}. Considering the results as they are, only about 20% of the selected nine sets of T_{min} extremes demonstrated significant increasing trends. Nevertheless, positive trend is evident in 7 of all the T_{min} extreme series studied. A significant increasing trend in T_{min} extremes for station {3} and that of rainfall extremes (Table 1), and a positive decreasing trend in T_{max} extremes for station {3} apparently demonstrates the physical nexus among the variables.

4.1.4. Extremes of streamflow

Table 4 provides results for the MK trend test on the AM streamflows (streamflow extremes) for seven selected streamflow stations. The definitions of the notations in columns (1)–(16) ware provided in Section 4.1.1. Table 4 shows that the streamflow extremes of 5 out of the 7 selected stations are positively skewed and are more variable than rainfall and temperature (T_{max} and T_{min}) extremes. The streamflow extremes can also not be assumed to follow a normal distribution. The streamflow extremes of the selected series are, all, significantly, serially correlated at the significant level of 0.05. Hence, the correction for the effect of serial correlation is vindicated for the MK test. Table 4 shows that all the extreme streamflow series have positive slope indicating that all the data have tendencies of increasing trends. The magnitudes of the values of the Sen's unit slope of all the selected stations are comparable to the magnitudes of the unit slope values for extreme series of rainfall and temperature with significant trends.

However, the P^* values indicate that no significant linear trend exist in the extreme streamflow series at the significant level of 0.05 or 0.01. Failure of the MK test to detect significant trends in the streamflow extremes is probably due to the higher values of the coefficient of variation and the differences in the distributions (and skewness) of the extremes. Yue et al. (2002a) noted that the power of the MK almost decreases exponentially with increase in

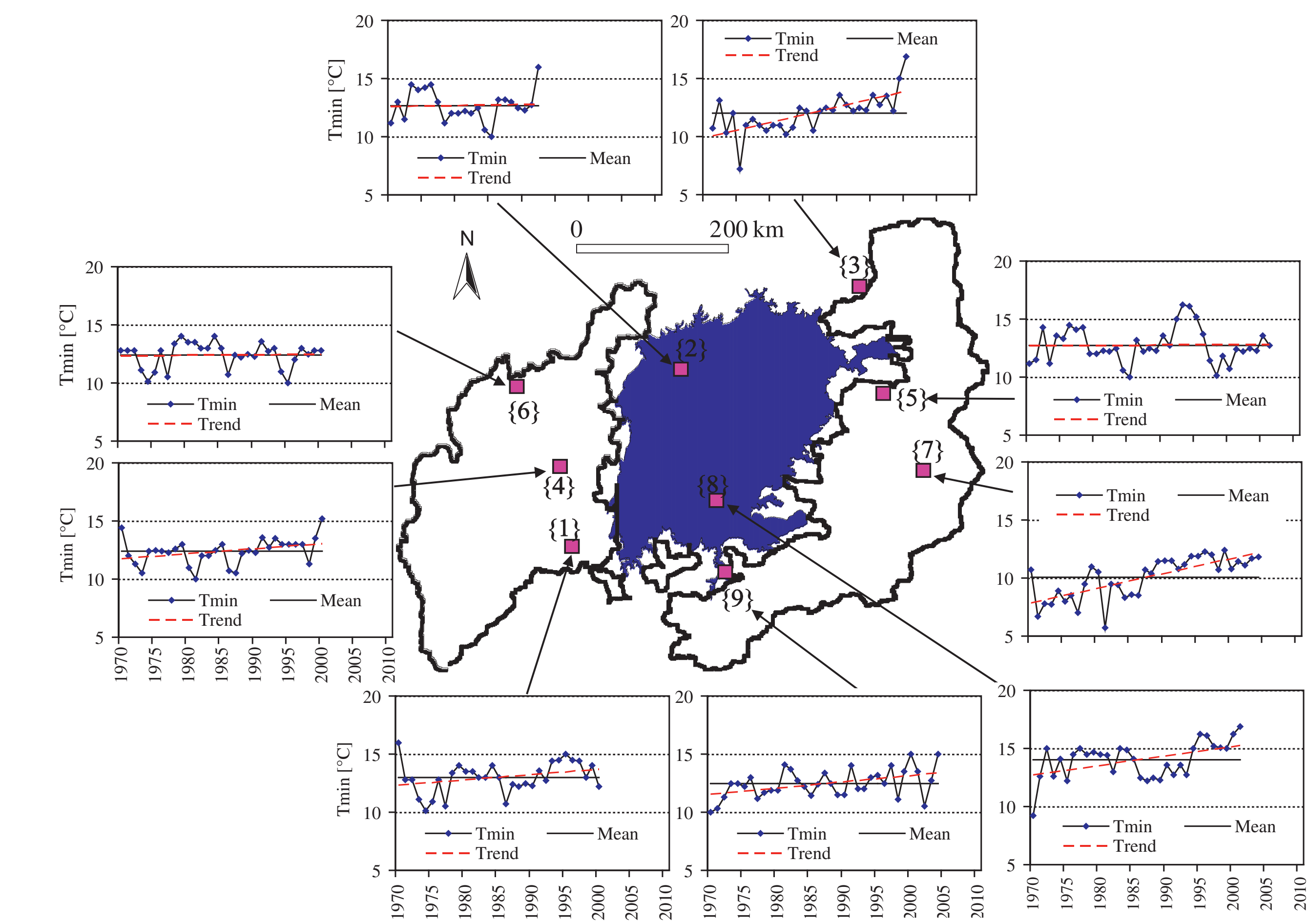

Fig. 6. Time series plots of the annual minima of T_{min} for selected temperature stations in the Lake Victoria basin.

Table 4
Basic properties and *P*-values of streamflow extremes for seven selected streamflow stations in the Lake Victoria basin.

Station (ID)	*n* (years)	n/n^*	Mean ($m^3\ s^{-1}$)	C_V	C_S	C_K	Correlation		Slope, *b*			*P*-value		*P*-value (R)	
							r_1	Limits Upper	(m^3/s/(per year)year) Lower		(11)/(4)	*P*	P^*	$P_{\alpha=0.05}$	$P_{\alpha=0.1}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
112022 [1]	28	1.8	202.9	0.283	−0.417	−0.566	0.289	0.316	−0.388	1.646	0.008	0.861	0.793	0.978	0.947
81248 [2]	45	16.4	22.3	0.430	0.338	−0.555	0.910	0.263	−0.307	0.118	0.005	0.792	0.580	0.968	0.945
81259 [3]	42	17.3	10.4	1.054	2.550	7.008	0.920	0.261	−0.309	0.013	0.001	0.577	0.519	0.976	0.951
104172 [4]	39	8.0	177.4	0.421	0.835	0.022	0.800	0.264	−0.315	0.875	0.005	0.856	0.647	0.973	0.946
1EF02 [5]	51	36.4	376.4	0.477	1.333	1.227	0.978	0.247	−0.286	2.032	0.005	0.967	0.620	0.980	0.956
81224 [6]	31	14.4	25.5	0.567	0.653	−0.672	0.910	0.300	−0.365	0.120	0.005	0.718	0.561	0.976	0.950
1AH01 [7]	43	12.6	56.1	0.176	−0.525	−0.495	0.878	0.251	−0.297	0.512	0.009	1.000	0.913	0.972	0.947

ID: Station identifier; *n*: actual sample size; n^*: effective sample size; C_V: coefficient of variation; C_S: coefficient of skewness; C_K: coefficient of kurtosis; r_1: lag-1 autocorrelation coefficient and its upper and lower limits of the confidence interval at the significant level of 0.05; *b*: slope of linear trend; *P* and P^*: the probability values, *P*-values, of the MK *S*, estimated from the original data, before correcting for lag-1 autocorrelation (*P*) and after correcting for lag-1 autocorrelation (P^*); *P*-values of the upper quartiles of the replicates of the data corresponding to 95% confident interval, $P_{\alpha=0.05}$, and 90% confident interval, $P_{\alpha=0.05}$.

the value of coefficient of variation of the data. The dependent of the MK power on a number of factors, especially on the site's statistical properties such skewness, which vary depending on the variable being analyse could have impacted on the existence of significant trends in extreme flow series for stations [5] and [7]. Visual inspection of Fig. 7 shows that the linear trends in the streamflow extremes are quite less amplified except of stations [1], [4] and [7].

4.1.5. Practical significance versus statistical significance

Yue et al. (2002a) discussed the relationship between statistical significance and practical significance, and they noted that a statistically significant trend may not be practically significant and vice versa. Adequately, large samples will definitely reveal any change, irrespective of the magnitude of change, using a statistical test, but the result may not render any help practically. Similarly, small samples of a given time series may not demonstrate a change statistically, but the amplitude of the change could be practically very significant. Consider, for example, the values of the unit slope for the streamflow and rainfall extremes presented in column (12) of Table 4 and in column (12) of Table 1, respectively. Although all rainfall extreme series have positive slope, only six stations out of the 10 stations have statistically significant upward trends. The slope of station (1) is not

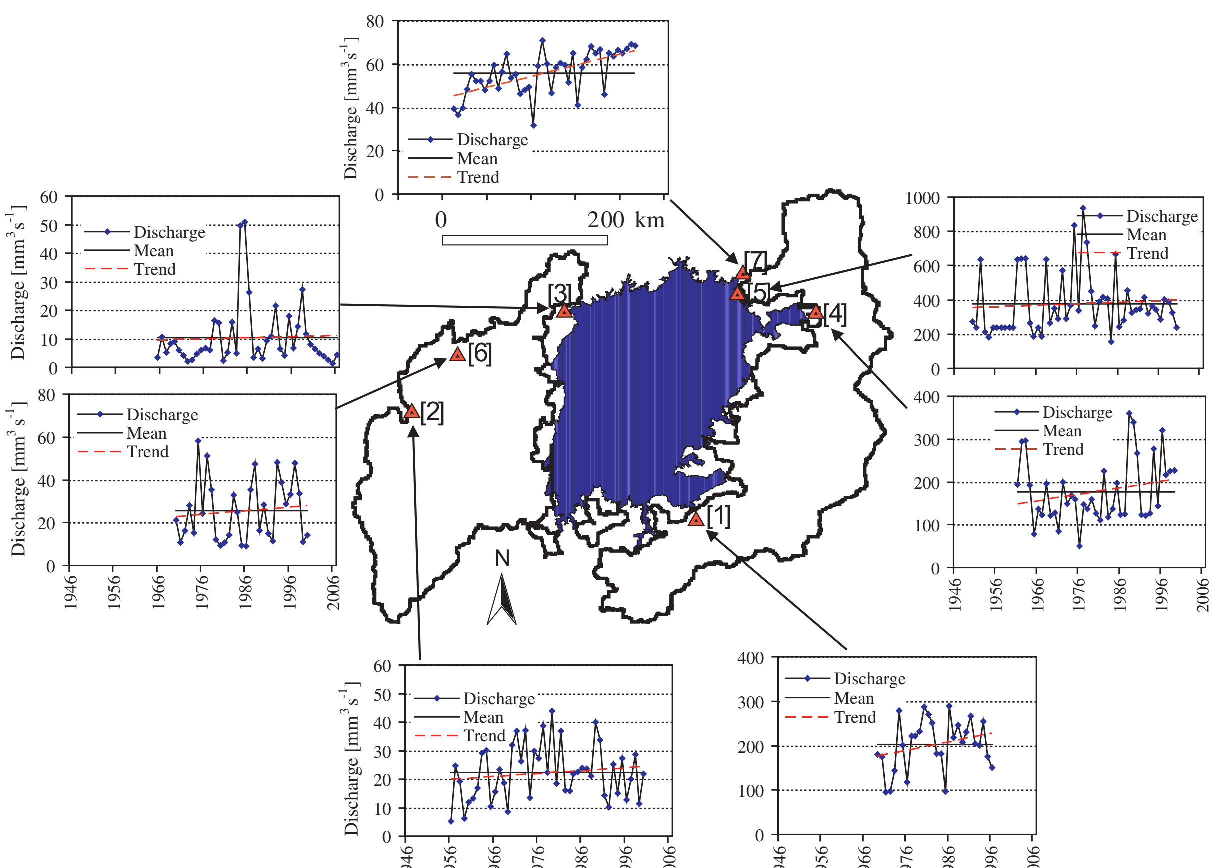

Fig. 7. Time series plots of the AM of the mean daily streamflow for selected streamflow stations in the Lake Victoria basin.

statistically significant and the visual inspection of chart representing station (1) in Fig. 4 shows little evidence of trend in the data. Over a 50-year period, for example, the slope yields an increase in the mean AM rainfall of 65.3 mm/day by about 1 mm/day or 1.5%. From a practical perspective, the estimated change is within the sampling error of the rainfall measurement and does appears, given the available data, not as being of practical importance. Similarly, the unit slope of trend for station (7) can yield 5.5 mm/day or 9.7% of the mean of 56.7 mm/day over a 50-year period. This is, also, within the sampling error. Furthermore, over a 50-year period, the unit slope of trend of magnitude 0.006212 per year for station (3) can yield 20.9 mm/day or 31.1% in the mean of 67.1. This is both statistically and practically significant and may not be ignored, assuming no possible reversal in the linear trend.

Trends in extreme streamflow series of stations [1], [5] and [7] are not statistically significant. Fig. 7 clearly shows the increasing tendency in trends. Table 4 shows that the streamflow extremes for the stations [5] and [7] have unit slopes of 0.00540 and 0.00912, respectively. Over a 30-year period, for example, the respective slope yields an increase of 60.9 $m^3 s^{-1}$ or 16.2% and 15.4 $m^3 s^{-1}$ or 27.4% of their mean of 376.4 $m^3 s^{-1}$ and 56.1 $m^3 s^{-1}$, respectively. Similarly, over a 28-year period, the slope of station [1] yields an increase in the mean of the extreme streamflow of 202.9 $m^3 s^{-1}$ by 46.1 $m^3 s^{-1}$ or 22.7%. These changes in the mean values of the streamflow extremes could be practically significant and need not be ignored despite the fact that significant trends were not demonstrated in the stream extremes.

It should be noted that beside detecting the existence of significant change in the past or recent climate (hydrometeorological time series) it is important to take heed to provide information to the engineer in charge of a water resources engineering project on the current attributes of, for example, the streamflow (e.g. AM and minimum, mean). However, even if the test shows a significant trend with a slope of practical importance, the engineer will only be vindicated in changing his assumption regarding the magnitude of the flow characteristic only if the change is permanent for the life of the project. Permanent change in streamflow characteristics is, mainly, attributed to change in climate and this can be reflected in the trends in temperature and rainfall. Despite the fact that no significant trend was detected in the selected extreme streamflows, in general, the identified trends appear to resonate fairly well with that of extreme series of rainfall and that of temperature.

4.2. Cyclic trend

4.2.1. Rainfall

Fig. 8 shows plots of percentage change (perturbation) for rainfall extremes together with the 95% confidence interval versus the year. Note that the reference perturbation represents the long-term expected rainfall extremes in the block periods following

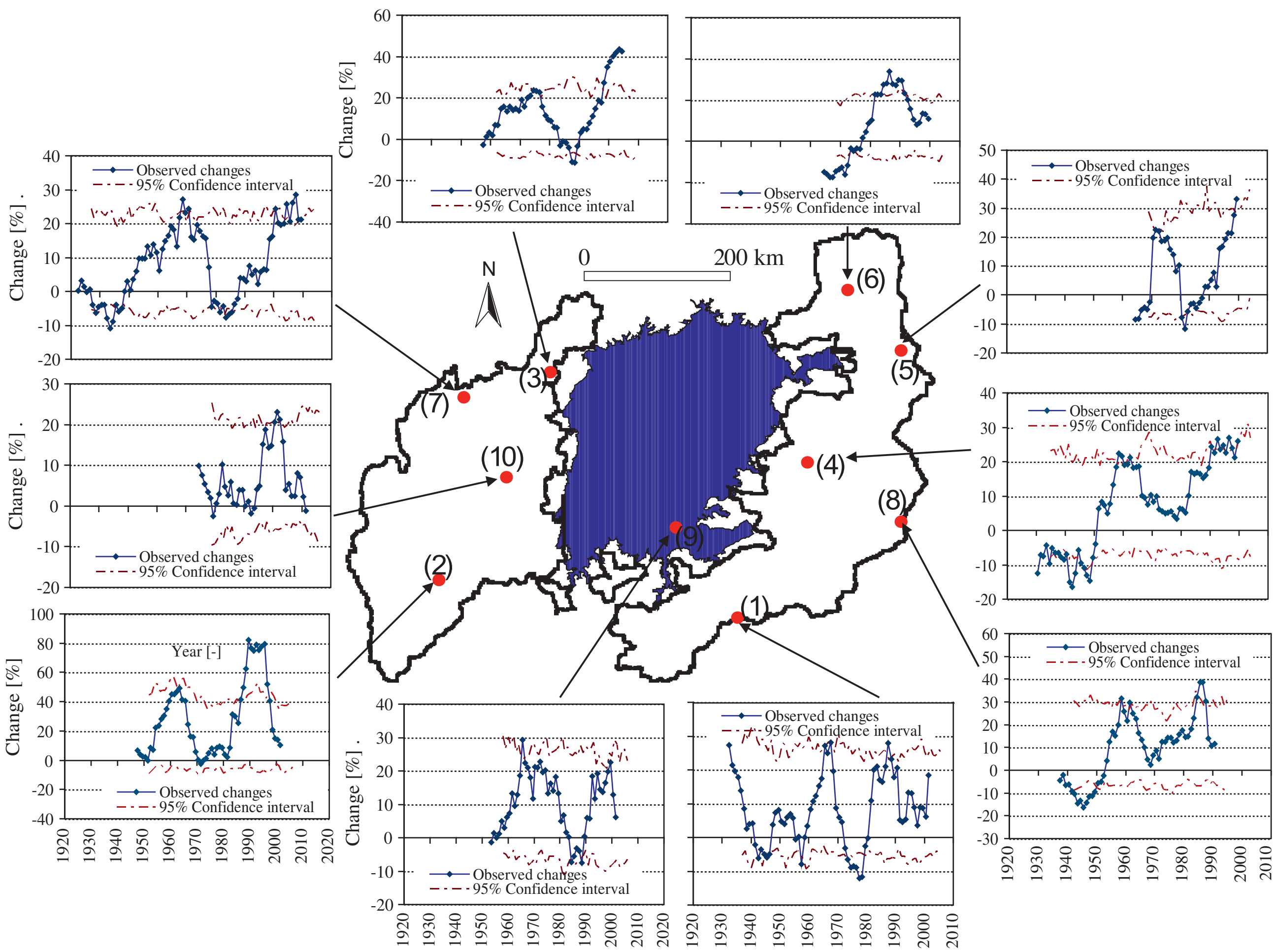

Fig. 8. Estimates of the average percentage change in the annual extreme quantiles of daily rainfall using a 10-year blocks, together with the 95% confidence intervals for selected rainfall stations over the Lake Victoria basin.

the total length of observed record. In addition, the reference provides the basis for testing the null hypothesis that the perturbations are not statistically significant from it. Fig. 8 also shows the locations of the rainfall stations for which the perturbations charts are related. The numbers in parentheses, ( ), are the IDs for the rainfall stations, as defined already in previous discussions. Perturbations of rainfall extremes, for selected rainfall stations, show some outstanding features of the observed rainfall characteristics in the Lake Victoria basin for the recent climate (Fig. 8). It can be seen from Fig. 8 that, all the selected stations indicate that, during the 1990s, the average perturbations fall outside the 95% confidence limits. This means that the null hypothesis is rejected at the significant level of 0.05. That is, 1990s experienced some dramatic high rainfall extremes over and above the expected natural variability. Similarly, apart from station (6) and station (10) of Fig. 8, whose records begin just after the 1960s, all others stations show that the rainfall extremes for the 1960s were significantly high. Further visual inspection of Fig. 8 also reveals that, given some of the selected stations, the 1940s and the 1970s received significant low rainfall extremes. However, it should be noted that the significant increase in the rainfall extremes observed in 1960s (up to 10–20%) is less than that observed in 1990s (up to 10–60%). Similarly, the significant low rainfall extremes observed in the 1940s (up to 20%) is much higher than that observed in the 1970s (up to 10%). This implies that the tendency for the rainfall extremes to shift towards positive change (high extremes) is evident. It is important to note that, in the Lake Victoria basin, significant increase and decrease in the rainfall extremes appear to occur after every cycle of about 32 years, given the data.

4.2.2. Streamflow

Fig. 9 shows estimates of the percentage change (perturbation) for streamflow extremes, together with the 95% confidence intervals. Apart from other stations, stations [3], [4], and [7] show some significant change in the streamflow extremes for the 1990s and statistically significant decrease for the 1970s. This is consistent with the anomalies for rainfall extremes. The mean cross correlation of the cross-correlation coefficients among the three streamflow stations is 0.105 and the upper and low limits of the 95% confidence interval of the two-tail *t*-test for correlation are 0.0943 and 0.0001. That is, the spatial correlations among the three stations are statistically significant and the pattern change in the observed streamflow extremes for the 1990s and 1970s could be by chance. Other factors, other than the primary factor of rainfall, also significantly influence the catchment response to hydrological extremes (e.g. Elferta and Bormann, 2010; Githui et al., 2009; McDonnell, 2009). This makes trend investigation on streamflow time series, in most cases, inconclusive.

4.2.3. Change correlations

Fig. 10a–c shows plots of perturbations for temperature (T_{max} and T_{min}) and rainfall for all the selected stations. It can be seen

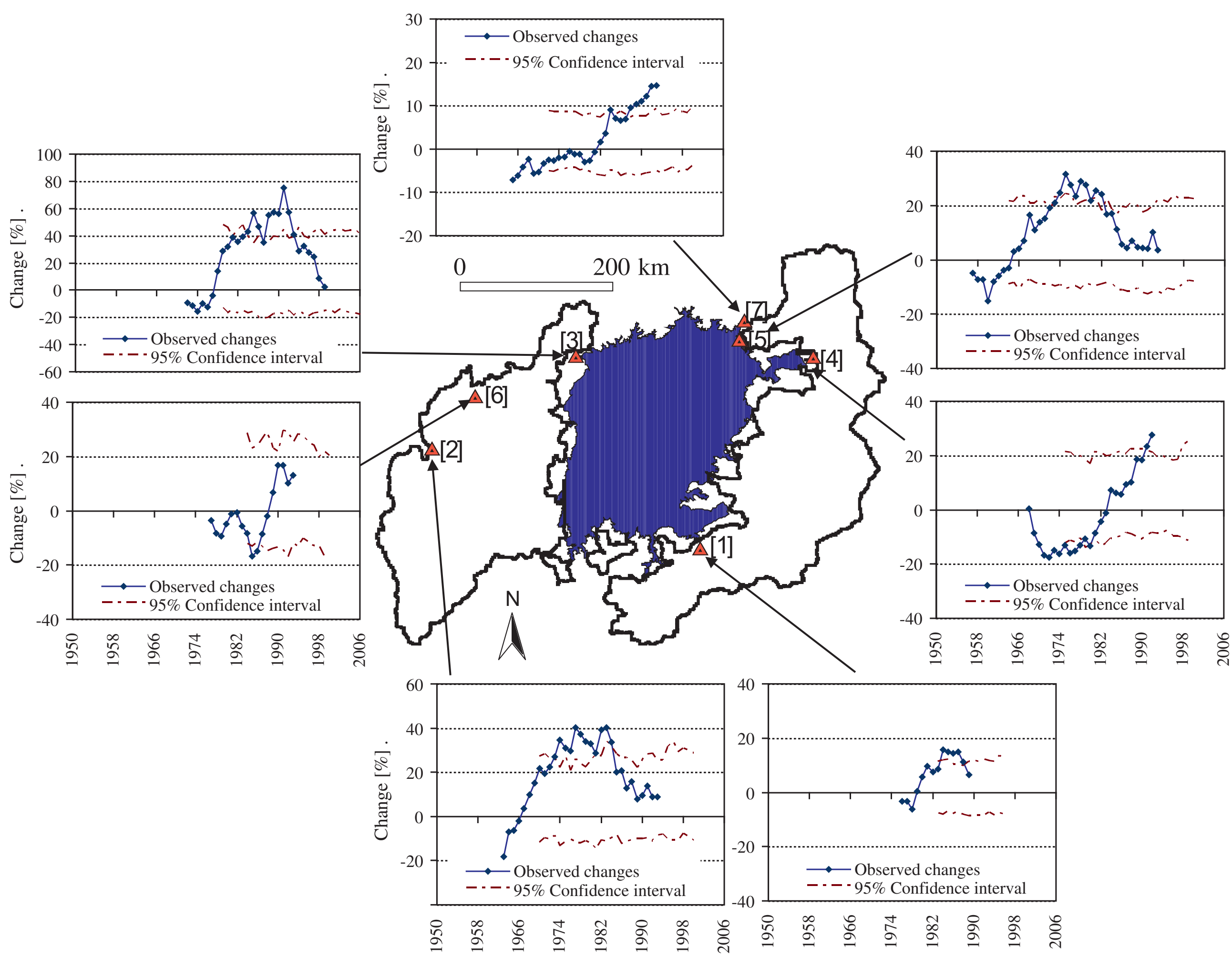

Fig. 9. Estimates of the average percentage change in the annual maximum quantiles of daily streamflow using a 10-year blocks, together with the 95% confidence intervals for selected minimum temperature stations in the Lake Victoria basin.

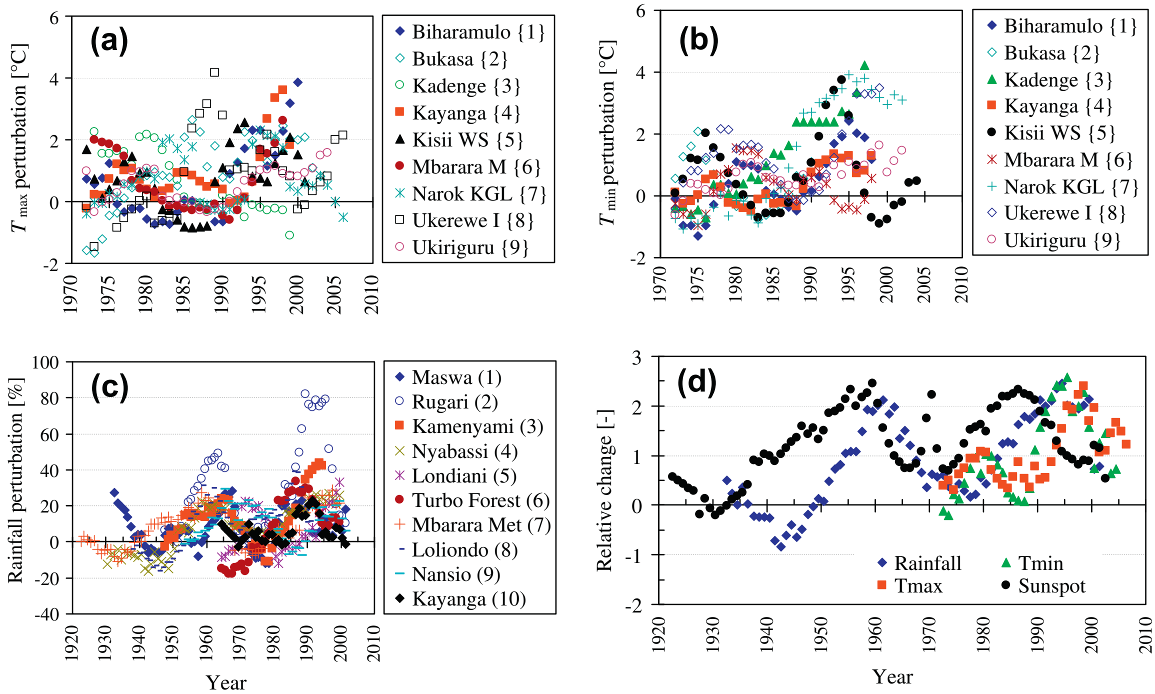

Fig. 10. Change in extremes for (a) T_{max}, (b) T_{min}, (c) rainfall, and (d) comparison of relative (normalized) change.

Table 5
Correlations between change in rainfall extremes and change in temperature maxima; and between change in rainfall extremes and change in sunspot maxima.

	T_{max}	T_{min}	Sunspot
Period	1970–2006	1970–2006	1940–2006
Correlation (–)	0.38	0.68	0.31

T_{max}: maximum temperature: T_{min}: minimum temperature.

from Fig. 10a and b that the perturbations for T_{max} and T_{min} also show that the anomalies for the 1990s were indeed higher. However, the perturbations for T_{min} for the different stations are more consistent for most of the years than that for T_{max}. Fig. 10c shows that perturbations for rainfall, for the different rainfall stations, are, generally, consistent for the 1940s, 1960s, 1970s and 1990s. The high and low cycles in temperature appear to be of shorter cycle length (in years) than that for rainfall. Fig. 10d shows the relative change in perturbations for rainfall, temperature (T_{max} and T_{min}) and sunspot maxima.

One very common feature in Fig. 10d is the similarity in the magnitude of the relative perturbation. In addition, the periodicity of the perturbation for sunspot and that of rainfall appear to resonate in some similar way from the 1950s to 1980s. It can also be seen that an apparent negative correlation between the temperature perturbations and that for the sunspot maxima is very prominent from 1980s to 2000s. These relationships mean that an increase in the temperature extremes is a manifestation of a decrease in the Sunspot maxima. A better indicator for the correlations in the perturbations between rainfall and temperature, and between rainfall and sunspot can be revealed by the respective correlation coefficients. Table 5 contains the values of the correlation coefficient between the perturbations for rainfall extremes and that of temperature and between the perturbations for rainfall extremes and sunspot maxima for the indicated periods. It can be seen that the value of the correlation coefficient (0.68) for the correlation between perturbation of rainfall and that for T_{min} is higher than that between rainfall and T_{max}, and that between rainfall and sunspot maxima. This means that there is a stronger correlation between daily rainfall extreme and the minimum of T_{min} than that between daily rainfall extreme and T_{max}. The relationship between change in rainfall extremes and sunspot maxima is weak. Fig. 11a shows the plots of change in rainfall extremes per unit change in temperature. In addition, Fig. 11b shows plots of change in rainfall extreme per unit change in sunspot maxima. In Fig. 11a, the

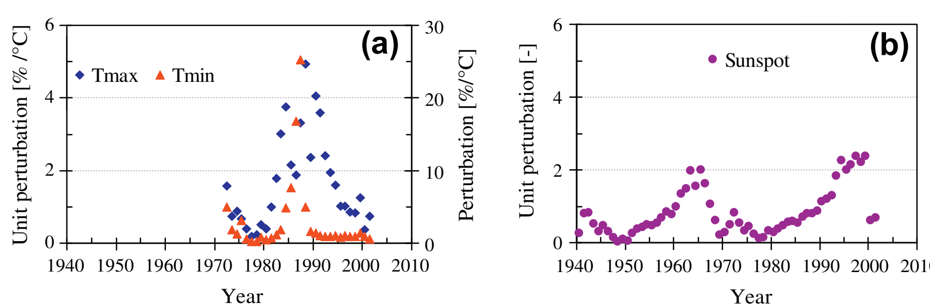

Fig. 11. Change in rainfall per unit change in: (a) temperature; and (b) sunspot maxima. The left ordinate in (a) is for T_{max} and the right ordinate in (a) is for T_{min}.

primary and the secondary ordinates are for T_{max} and T_{min}, respectively. It can be seen that a change in the T_{min} extreme by 1 °C causes the rainfall extreme to change by higher percentage (up to 25%) than a change in the T_{max} extreme for the observed periods 1970s–2006. Fig. 11b shows that, given the available data, change in the sunspot maxima cannot cause rainfall extremes to change by more than 3%.

4.2.4. Hydroclimatic correlation with climate indices

Investigating the causes of the variability in the hydroclimatic extremes with the use of statistical correlation analysis gave results as presented in Figs. 12 and 13 and Table 6. Fig. 12 contains plots of annual anomalies in the selected climate indices together with the 95% confidence interval for the period 1900–2010. Fig. 12 shows that the PDO and AMO anomalies were significant in the 1930s (high), 1950s (low) and 1980s (high). If charts in Fig. 12 are compared with those in Fig. 8 we find that PDO and AMO resonate negatively with the extremes of rainfall. Fig. 12 also shows that the SOI anomalies were significant in the 1940s (low), 1960s (high), 1980s (low) and 1990s (high). The trends o the anomalies in SOI are strongly similar to those of rainfall extremes (Fig. 8) which is an indication a strong correlation between rainfall extremes SOI. The trends of the IOD anomalies relatively follow those of the SOI (Figs. 12 and 13). The observed oscillations in the climate indices showed that PDO and AMO resonate negatively with extremes of rainfall, while SOI and IOD resonate positively with rainfall extremes. The frequency of occurrence of the oscillations (high and low) for the PDO and SOI anomalies are higher compared to those of IOD and AMO (Fig. 13). Table 6 contains the statistical significance of the correlation coefficients at 1% and 5% significance levels based on the t-test. Table 6 shows that there is no consistent correlations between the climate indices and the rainfall extremes observed different locations in the Lake Victoria basin. However, rainfall extremes from station (4), (5) and (9) show some consistence positive correlations with SOI and IOD. Table 6 further shows that it is not possible to make strong conclusion on the linkages between rainfall extremes observed at different locations in the Lake Victoria basin and anomalies in the selected climate indices because of the inconsistent correlation between them. Thus, rainfall extremes observed in Lake

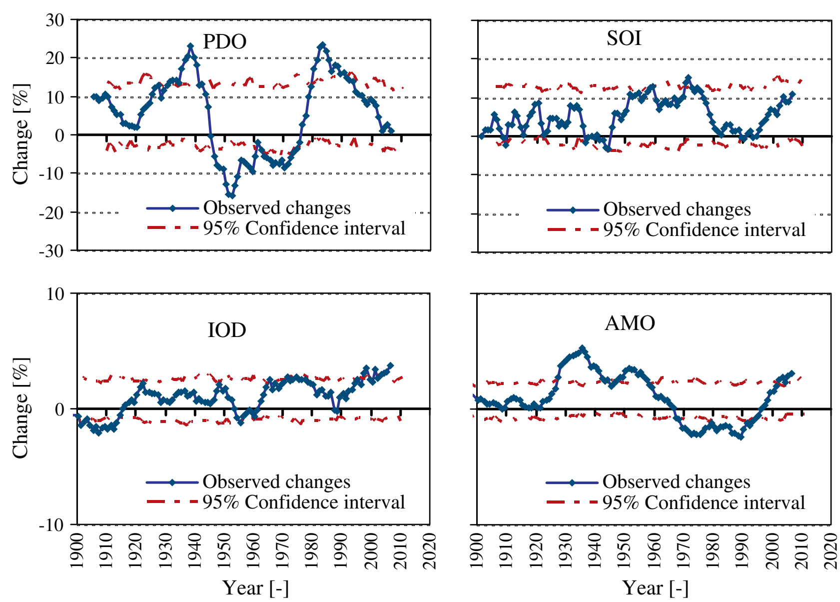

Fig. 12. Annual oscillation of the anomalies of the climate indices for a block length of 10 years: PDO, Pacific Decadal Oscillation; SOI, Southern Oscillation Index; IOD, Indian Ocean Dipole; AMO, Atlantic Multidecadal Oscillation.

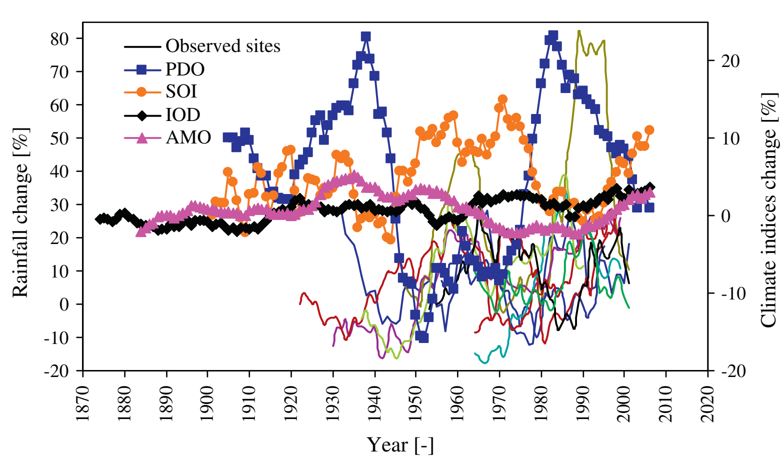

Fig. 13. Comparison of the annual oscillations of the anomalies of the climate indices with those of the rainfall extremes observed in the Lake Victoria basin: PDO, Pacific Decadal Oscillation; SOI, Southern Oscillation Index; IOD, Indian Ocean Dipole; AMO, Atlantic Multidecadal Oscillation.

Table 6
Annual correlation coefficients between rainfall and temperature extremes and climate indices.[a]

Station	Temperature	Rainfall				T_{max}				T_{min}			
Rainfall		PDO	SOI	IOD	AMO	PDO	SOI	IOD	AMO	PDO	SOI	IOD	AMO
(1)	{1}	0.240	−0.159	0.001	−0.018	−0.149	0.205	0.494[b]	0.783[b]	0.394	−0.625[b]	0.128	0.743[b]
(2)	{2}	0.416[b]	−0.559[b]	−0.260	−0.181	0.634[b]	−0.667[b]	−0.179	0.396	0.631[b]	0.648[b]	0.399	−0.633[b]
(3)	{3}	−0.484[b]	0.273	−0.249	0.583[b]	−0.512[b]	0.439[c]	0.186	−0.515[b]	0.532[b]	−0.613[b]	−0.062	0.655[b]
(4)	{4}	−0.054	0.175	0.091	−0.577[b]	−0.003	0.075	0.498[b]	0.759[b]	0.723[b]	−0.179	0.364	0.630[b]
(5)	{5}	−0.222	0.322	0.590[b]	0.159	−0.509[b]	0.123	0.487[b]	0.387[c]	0.134	−0.142	0.008	−0.254
(6)	{6}	0.948[b]	−0.851[b]	−0.587[b]	−0.249	−0.614	0.745[b]	0.845[b]	0.413[c]	−0.582[b]	−0.553[b]	−0.307	0.015
(7)	{7}	−0.249	−0.023	−0.222	−0.127	0.275	−0.336[c]	0.076	0.025	0.603[b]	−0.430[c]	0.084	0.629[b]
(8)	{8}	0.151	0.263	−0.114	−0.543[b]	0.637[b]	−0.515[b]	−0.319	0.155	0.474[c]	0.000	0.621[b]	0.836[b]
(9)	{9}	−0.391[b]	0.353[c]	0.660[b]	−0.101	−0.316	0.229	0.666[b]	0.701[b]	0.359	−0.355	0.193	0.669[b]
(10)		0.266	−0.433[b]	−0.529[b]	−0.184								

[a] PDO, Pacific Decadal Oscillation; SOI, Southern Oscillation Index; IOD, Indian Ocean Dipole; AMO, Atlantic Multidecadal Oscillation.
[b] Statistically significant at 1% significance level.
[c] Statistically significant at 5% significance level.

Victoria basin, cannot only be explained by these climate indices but also by other influences that could be playing a major role on the occurrence of extreme rainfall in the basin. Nevertheless, the QPMtc method provided some better and consistent results than the *t*-test method. Table 6 shows that the relationships between IOD and AMO and the observed temperature extremes are more consistent compared to those of observed rainfall extremes. The correlations between IOD and AMO and temperature extremes are positively stronger and statistically significant at 1% significance level. This means that for a long-term prediction of temperature extremes, the climate indices (IOD and AMO) may be used.

AMO shows less strong but significant correlation with the long rainy season rainfall and flow variability. Conversely, AMO shows strong and significant correlation during the dry season.

IOD has a weak correlation with the extremes in all the seasons and at annual scale. From this analysis it is concluded that the extreme rainfall and flow of the upper Blue Nile basin is influenced by changes that occur on both the Pacific and Atlantic Oceans.

5. Conclusions

The MK test was applied to detect the existence of statistical significance linear trends in the extreme time series for daily rainfall, streamflow and maximum and minimum temperatures for selected stations in the Lake Victoria basin. The record lengths of the selected stations vary from 47 to 87, 28 to 51, 31 to 39, and 23 to 37 years for rainfall, streamflow, maximum temperatures and minimum temperatures, respectively. The data records of most of the stations date up to 2006. The magnitude of the gradient of the linear trend was estimated using Sen's slope estimation technique. In general, the presence of positive linear trends dominates the extreme series of all the variables.

For rainfall extremes, all the selected stations demonstrated increasing trend of positive slopes, indicating that increase in the observed rainfall extremes in the study area is prominent. Of the 10 selected rainfall stations, six demonstrated the presence of significant positive trend. Thus, given the available data, the rainfall extremes in the Lake Victoria basin, for the past 3–8 decades, had a general upward trend. Given the fact that the study used relatively longer records of rainfall series, the presence of significant upward trend in the extremes fairly demonstrates the trend in the climates of the recent decades in the Lake Victoria basin. Of the nine selected stations, for maximum daily temperature, seven demonstrated the present of increasing trend while two demonstrated decreasing trends. The existence of statistically significant increasing trend was exhibited by only one station. Meanwhile, all the three stations, with negative slope, were not statistically significant. For daily minimum temperature, the presence of increasing trends was demonstrated in 7 out of 9 stations. Two stations had stationary slope. Significant positive trend was demonstrated only in two stations. Irrespective of the significance of the trend, an upward trend is thus more demonstrated in the annual extremes for minimum daily temperature than that for maximum daily temperature.

The evidence of the presence of increasing trend in the streamflow extremes of all the seven selected streamflow stations was demonstrated by positive slope. No significant trend however was detected in all the seven streamflow extreme series. Given that statistically significant trend does not necessarily imply trend of practical significance and vice versa, in overall, 6 of the 7 streamflow stations, with statistically insignificant upward trend, demonstrated slopes of practical importance. With these statements, we can conclude that there is reasonable evidence of positive change in the extreme climate of the Lake Victoria basin as demonstrated by the presence of linear trends in the hydrometeorological extremes.

Analysis of cyclic trends in hydrometeorological variables provides an opportunity for situating the characteristics of the observed changes into climate change perspective. The robust nature of the methodology used in the analysis, the quantile perturbation, provides the possibility of the identifying of significant temporal changes. The cyclic flaunts of the results is a very good way of providing information on the amplitudes of the temporal changes in the observed hydrometeorological extremes and probable evidence on the direction of change. In addition, it was possible to compare relative change in rainfall extremes with the relative changes in the daily maximum temperature as well as that of sunspot maxima. The statistically significant anomalies in the rainfall extremes for the recent decades are evidences of a more intensification of rainfall in the recent past, observed in the 1990s compared to 1960s. The block occurrence of rainfall extremes, in time, is an evidence of the fact that wet decades tend to be followed by dry decades leading to some kind of clustering of extremes. From the available data, the emergence of high and low extremes, in time, as evidenced in rainfall extremes, is an approximate cycle of about 32 years for the Lake Victoria basin. Given the available data, changes in maximum and minimum temperature extremes tend to resonate fairly well with the changes in the rainfall extremes. This change resonance was also evidence in sunspot maxima but with weaker signals. A unit change in minimum daily temperature causes a much higher change in rainfall extreme than a unit change in maximum temperature. A unit change in sunspot maxima does not cause any significant change in rainfall extremes. In addition, there is a stronger correlation between change in rainfall extremes and that of the minimum temperature, compared to that maximum temperature and sunspot maxima. This suggests that the change in the minimum of the daily minimum temperature is a better indicator for change in rainfall extremes for the Lake Victoria basin.

The investigation of the correlations between climate indices and hydrometeorological extremes suggests that oceanic influences are part of the explanation of the variability observed in rainfall and temperature extremes in the Lake Victoria basin. The changes in the Indian and Atlantic oceans have some influences on the observed decadal cyclic trends on the hydrometeorological extremes in the Lake Victoria basin. Understanding the relationships between the trends in the climate oscillations and those of the hydrometeorological extremes is very important for planning for water and agricultural management as well as predicting risks associated with the extremes. The relationships between climatic indices and hydrometeorological extremes might likewise be important in extrapolating temporal anomalies in rainfall extremes for stations with shorter record lengths given that the large scale climate drivers such as the SOI have long historical records. The QPMtc method used in this study demonstrated its capacity to study hydrometeorological extremes, as the results found were very transparent and consistent. It is apparent that such information would be very important for water and agricultural manager involved in predicting and managing risks associated with hydrometeorological extremes such as floods and droughts. The natural variability at decadal time scales can also be filtered out from the long-term trends due to global influences and to predict upcoming periods with high or low climatic anomalies.

Acknowledgements

This research was conducted at Hydraulics Laboratory of Katholieke Universiteit Leuven, Belgium, in collaboration with the Department of Civil Engineering, Makerere University Kampala, Uganda. The Flemish Interuniversity Council (VLIR) of Belgium financially supported the research. The research work is linked to the research activities of the FRIEND/Nile Project funded by the Flemish Government of Belgium through the Flanders-UNESCO Science Trust Fund cooperation and executed by UNESCO Cairo Office.

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