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Drought monitoring and analysis: Standardised Precipitation Evapotranspiration Index (SPEI) and Standardised Precipitation Index (SPI)

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ABSTRACT

Although rainfall is a major indicator of the availability of water, temperature is also an important factor that can influence the availability of water as it controls the rates of evapotranspiration. Parameters such as rainfall and temperature can be used as indicators of drought. These indicators are converted to drought indices which show the different characteristics of a drought. This study compares two different drought indices in the Kafue Basin located in northern Zambia, where most of the socioeconomic livelihoods are dependent on water. The Standardised Precipitation Index (SPI) depends on precipitation as the single input variable while the Standardised Precipitation Evapotranspiration Index (SPEI) is derived from precipitation and temperature in the form of a simple water balance. By comparing time series plots (1960–2015) of the two indices, both indices were able to pick up temporal variation of droughts. SPI and SPEI agreed ($R > 0.5$) on the direction of change but the effect on the drought condition was different. Compared to SPI, SPEI identified more droughts in the severe to moderate categories, with extended duration and increased intensity. On the other hand, SPI identified more droughts than SPEI under the extreme category, but with a shorter duration and reduced frequency of occurrence compared to the severe to moderate droughts. The results suggest that temperature variability plays an important role in characterising droughts. SPI is useful in that it only requires rainfall as input and especially where temperature data is missing. However, the use of SPI to characterise drought should be done with caution.

1. Introduction

Hydrologically extreme events such as floods and droughts are placed high on the list of climate-related natural disasters. Drought in particular is one of the biggest threats to human survival, imposing serious adverse impacts to social, economic and environmental sustainability (Sharma et al., 2009). Defining a drought is complicated by the fact that droughts are spatially and temporally variable, region-specific, context-dependent, and because they occur with varying degrees of intensity, whilst their cumulative effect makes it difficult to identify their start and end (Quiring and Papakryiakou, 2003). A drought can be defined simply as a recurrent and natural climatic event caused by below normal precipitation compared to the long-term average and extending over a long period of time (Kundzewicz, 1997; Pandey et al., 2007; Dai, 2011).

Compared to floods, droughts develop slowly over time and are only recognized once people and the environment start to feel their impact (Vicente-Serrano and Lopez-Moreno, 2005). As a result, it is difficult to determine the onset and cessation of droughts. Defining droughts is also complicated by the fact that they are widespread in occurrence and complex in nature. Initially occurring as a result of prolonged below normal precipitation, droughts may have implications on other components of the hydrological cycle. Therefore, it is possible for one type of drought to convert into another type under prolonged occurrence. In relation to water resources, drought can be considered as a multi-scalar phenomenon which is guided by catchment response time. It is worth noting that the hydrological responses of soil moisture, river discharge and groundwater recharge as well as the biological response of crops and natural vegetation vary and have different response times (Lorenzo-Lacruz et al., 2010). Therefore the time over which the water deficits accumulate (timescale) is very important in determining the prevailing type of drought (Wilhite and Glantz, 1985; Howard et al., 2014). Timescales functionally separate the different types of droughts into meteorological (1 month timescale), agricultural (3–6 month timescale) and hydrological droughts (12 month timescale) (Vicente-Serrano et al., 2010; Homdee et al., 2016). It is therefore important that droughts are classified by the specific timescales to allow proper assessment of the drought.

The rate of evapotranspiration is mainly influenced by temperature, atmospheric evaporative demand and the effect of heat waves (Beguería

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et al., 2014; Vicente-Serrano et al., 2015). Temperature is one of the major climatic factors that influences availability of water and also has consequent effects on the nature and occurrence of droughts (Rebetez et al., 2006; Dubrovsky et al., 2008, Sheffield and Wood, 2008. Already some studies project an increasing trend in global mean annual temperatures (e.g. Trenberth et al., 2007; Dai, 2013; Trenberth et al., 2014). Moreover, in most arid and semi-arid regions of the world potential evapotranspiration is higher than annual precipitation such that a precipitation-only based drought index may not be sufficient to monitor droughts (Howard et al., 2014; Hogg, 1994). It is therefore important to incorporate temperature and/or other hydrological components in the determination of drought indices. Although it is difficult to identify the onset and cessation of droughts, their impacts can be averted through an understanding of their nature and occurrence. As such, appropriate and timely interventions to the impacts of droughts require monitoring tools that are able to objectively quantify the intensity, duration, magnitude and spatial extent of droughts (Smakhtin and Hughes, 2004).

Since drought is related to climatic events, variables such as rainfall, temperature and streamflow can provide good indicators of the occurrence or non-occurrence of drought. These indicators can then be converted to drought indices which show the occurrence, magnitude, intensity and duration of a drought event (Zargar et al., 2011; Hayes, 2006). Drought indices can either be formed from a single input variable or from a combination of hydrological variables (Hao and Singh, 2018). Indices composed of a number of hydrological variables tend to provide more certain results, however, what variables to use depends on the situation to be addressed and the type of drought under analysis. Furthermore, selection of the drought index is guided by the region of interest and data availability (Smakhtin and Schipper, 2008).

Several drought indices are in existence (Heim, 2002), but so far the most commonly used drought indices are the Palmer Drought Severity Index (PDSI, Palmer, 1968) and the Standardised Precipitation Index (SPI, Mckee et al. (1993). The PDSI is based on a simplified water balance with input parameters of precipitation, runoff, moisture supply and evaporation. On the other hand the SPI is a simplified index with only one input variable; precipitation (Vicente-Serrano et al., 2010). A drought index which is able to account for the different timescales and the spatial scale at which drought occurs is considered to be multi-scalar in nature (Guttman, 1998). The SPI incorporates cumulative precipitation deficits at various spatio-temporal scales, thus rendering it multi-scalar (Hou et al., 2007). A major assumption in the computation of SPI is that droughts are largely driven by rainfall variability while other factors such as temperature are assumed to be stationary and as such do not change over time (Vicente-Serrano et al., 2010). The fundamental strength of SPI over other indices is that it is able to detect drought at different time scales (1, 3, 6, 12 and 24 months) implying that various types of drought (meteorological, agricultural and hydrological) can be monitored. However, the quality of a drought index result can only be as good as the input data (Tirivarombo and Hughes, 2011).

Although the PDSI incorporates components of the hydrological cycle in its formulation, it falls short of the multi-scalar characterisation of droughts because it is not capable of identifying drought for different timescales. Moreover, many parameters are required to calculate the index (Vicente-Serrano et al., 2010). The SPI is multiscalar but only incorporates precipitation to calculate the drought index. On the other hand, SPEI is a multi-scalar drought index which also takes into consideration both precipitation and temperature in addition to the ability to identify drought at different time scales. Because of its ability to incorporate both temperature and precipitation, SPEI may be a useful indicator of drought (Howard et al., 2014), considering that evapotranspiration is the major form of water loss in dry regions where temperatures are high. The index is calculated based on the non-exceedance probability of the differences between precipitation and potential evapotranspiration, adjusted using a three-parameter log-logistic distribution which accounts for common negative values (Středová et al., 2011; Vicente-Serrano et al., 2010).

Droughts are a common and recurrent feature in southern Africa which can have detrimental effects on the natural environment and agriculture with repercussions on human socio-economic well-being. A large proportion of the population in the region depends solely on rainfed agriculture for survival and in addition to agricultural demand there is increased pressure on water resources in the region due to population expansion and new developments. It is therefore important to have in place adequate drought assessment and monitoring tools that can produce reliable results to assist decision making at all levels. Because of the different formulations of the SPI and SPEI, this study seeks to compare the SPI and SPEI in characterizing droughts using a case example of the Kafue sub-basin which is found in Zambia. The basin drains into the Zambezi River and it is important because of its economic, social and ecological importance. About 50% of Zambia's population lives in the basin and relies on the basin's water resources for various uses such as mining, industry and agriculture. Despite heavy reliance on the basin's water resources, the basin is under threat of high natural climatic variability which is amplified by climate change thus increasing the occurrence of hydrologically extreme drought events (Lweendo et al., 2017).

2. Materials and methods

2.1. Study area

The Kafue basin (Fig. 1) occupies an area of about 156 995 km^2 which is about 20% of Zambia's total land area. With a length of 1300 km, the Kafue River is one of the major tributaries of the Zambezi River. Among other important features, the Kafue basin hosts the Kafue Flats, a wetland which falls under the RAMSAR Convention. The soils in the basin are a dark clayey montmorillonite characterized by high water holding capacity. The basin experiences two distinct seasons; a wet season and a dry season extending from November to April and from May to October respectively. Mean daily temperatures range between 13 °C and 20 °C in winter and between 21 °C and 30 °C in summer. Rainfall is largely influenced by the Inter Tropical Convergence Zone (ITCZ) which is a low-pressure system caused by the convergence of trade winds. The position of the ITCZ varies from year to year thus influencing the precipitation patterns in the basin. The annual rainfall ranges from 1300 mm/year in the north to 800 mm/year in the southern parts of the basin. The basin experiences an average annual potential evapotranspiration rate of about 1300 mm/year with highest monthly values from August to November at about 200–300 mm/month. Rainfall distribution is spatially variable in the Kafue basin, decreasing in a north-south direction (Lweendo et al., 2017). Therefore, the northern sub-basins consisting of Lufwanyama, Luswishi, Lunga and to some extent Kafue 4 receive more rainfall than the southern-most sub-basins.

About 50% of Zambia's population is concentrated in the Kafue basin and most of the communal livelihoods depend on rainfed agriculture for sustenance, implying that the basin community is vulnerable to the impacts of changing rainfall patterns as a result of climate variability and change. In addition, two major dams, the Itezhitezhi and the Kafue Gorge are found within the basin and are used for generating hydroelectricity. Other major activities in the basin include mining and industry which also impose a large water demand on the basin's water resources (Mfalila et al., 2013).

2.2. Climate data

Due to sparse rainfall gauging networks this study used CRU TS4.00 data as an alternative dataset which was obtained from the Climate Research Unit of the University of East Anglia (Harris and Jones, 2017). The data set consists of 0.5° grids of monthly time series of different

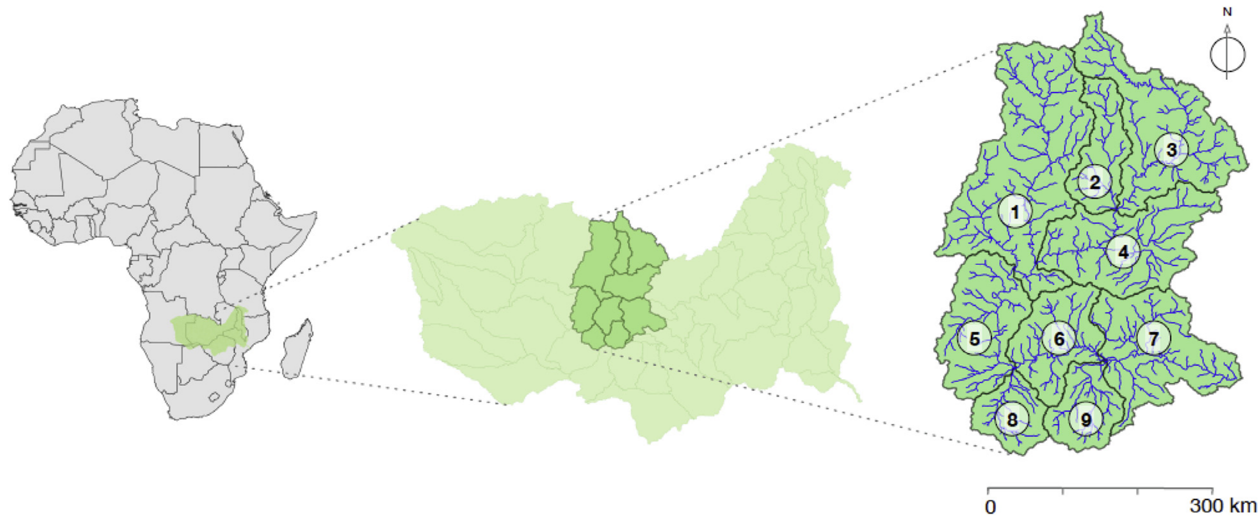

Fig. 1. Location of Kafue basin. Sub-basins: (1) Lunga, (2) Luswishi, (3) Lufwanyama, (4) Kafue 4, (5) Kafue 3, (6) Kafue 2, (7) Kafue 1, (8) Nanzhila and (9) Kasaka.

climate variables including rainfall and temperature for the period 1901–2015. Ground station datasets with a long enough time series which includes a base period of 1961–1990 are used to calculate monthly normals after which the ground station data is converted into anomalies by subtracting the 1961–1990 normal from the respective station's time series data for each month (Willmott and Robeson, 1995). The temperature and rainfall gridded datasets are obtained by direct estimation through interpolation (as a function of latitude, longitude, and elevation) from the ground station data (Harris et al., 2014) as obtained from the respective countries' meteorological stations. To correct for inhomogeneity in data for any station, reference (1961–1990) time series data from neighbouring ground observation stations are used for comparison against the station in question. Anomalies relative to the 1961–1990 mean of the nearby ground station data are interpolated and combined with the gridded anomalies. Using the angular distance weighting method (New et al., 2000) these gridded anomalies are then combined with the mean monthly (1961–1990) climatology to obtain the monthly climate grids for the period 1901–2015.

The reliability of the CRU data was assessed based on ground rainfall stations (Table 1) that are representative of the various sub-basins, with reasonably long time series (> 30 years) and nearest to selected grid points. The correlation results, which are a combination of all the stations used in the analysis and averaged to represent a basin composite result for the various months are shown in (Fig. 2). In general most of the data points lie within the 95% confidence band and overall the relationships between the CRU data and the ground station data are assumed to be reasonably good ($R^2 > 0.5$) thus providing confidence in the use of the CRU TS4.00 data.

Analysis at the sub basin or basin scale requires catchment averaged rainfall which has an advantage over point or gridded data because local variabilities associated with specific stations are eliminated (WMO, 2000). For each sub-basin, the inverse distance weighting method (Wilk et al., 2006) is used to calculate the weighted average rainfall and temperature from the CRU climate grids found within each sub basin using the equation:

$$R = \sum \frac{R_i}{d_i^2} / \sum \frac{1}{R_i{}^2} \tag{1}$$

where, R is the estimated rainfall for a specific sub basin, R_i is the rainfall at a grid point, i, and d is the distance between the centroid of the area and the grid point.

Potential evapotranspiration was estimated by the Thornthwaite method (Thornthwaite, 1948). This method was chosen due to the fact that out of the climatic variables required for estimating potential evapotranspiration we had temperature data at our disposal and the Thornthwaite method requires only temperature as the input variable (equation (2)).

$$PET = 16d\left(\frac{10T}{I}\right)^a \tag{2}$$

where: T (°C) is the mean temperature for the month, d is the correction factor to account for the unequal day length between months and is read from tables based on the latitude of the study area.

I represents the annual thermal index and i is the monthly thermal index.

$$\mathrm{I}= \sum_{j=i}^{12} i \tag{3}$$

$$i = \left(\frac{\mathrm{t}}{5}\right)^{1.514} \tag{4}$$

$$a = 0.49 + 0.018I - 7.7\,x\,10^{-5}I^2 + 6.7\,x\,10^{-7}I^3 \tag{5}$$

Table 1
Kafue ground stations used to validate the CRU TS4.00 data.

Sub-basin	Latitude	Longitude	Record years
Lunga	−12.1	26.4	1906–1994
Luswishi	−12.9	27.36	1951–1987
Lufwanyama	−13.2	28.29	1906–1964
Kafue 2	−15.8	26.5	1919–1987
Kafue1	−15.87	27.76	1916–1986
Kasaka	−15.98	27.6	1946–1996

2.3. SPI and SPEI drought indices

A comparative analysis of SPI and SPEI is carried out in order to establish whether potential evapotranspiration has an effect on the drought index. The analyses were done at different time scales for the period 1960–2015. The different time scales (1, 3–6, and 12 months) represent meteorological, agricultural and hydrological droughts respectively. The SPI and SPEI were generated using the SPEI package (Bergueria et al., 2014) found in the R software package which is a free software environment for statistical computing and graphics, this package provides different options for calculating SPI and SPEI.

2.3.1. SPI

The SPI was designed to assess drought conditions based on the

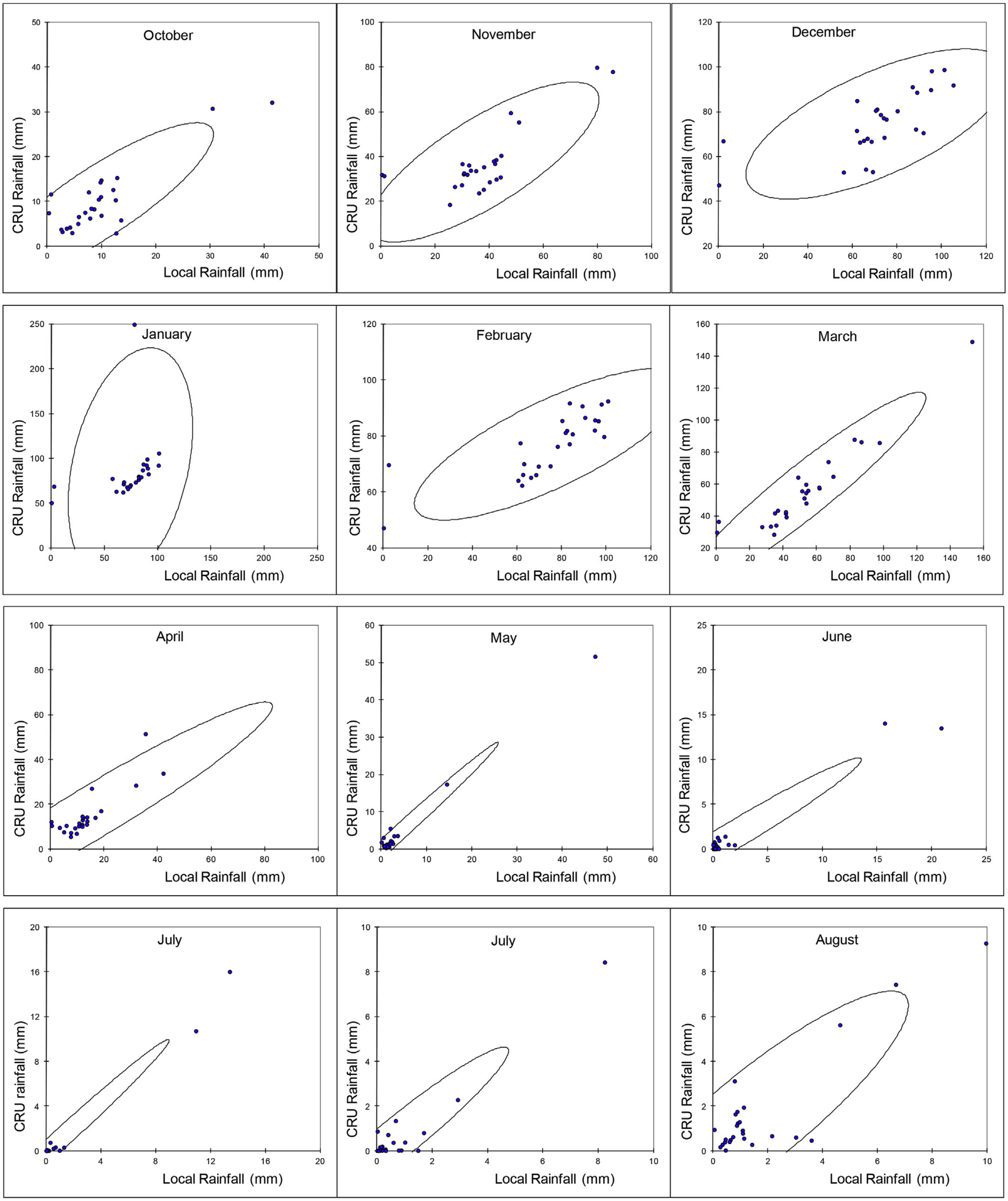

Fig. 2. Comparison of CRU TS4.00 rainfall data and local rainfall data (based on long-term mean monthly rainfall for various stations and averaged for the whole basin, lines show 95% confidence bounds).

probability distribution of long term precipitation using the gamma function (McKee et al., 1993). Precipitation is transformed into normalised numerical values and the SPI is given as the number of standard deviations by which the observed precipitation deviates from the long-term mean for a normally distributed random variable (equation (6)). It can thus be used to define and compare drought conditions in different areas. The index gives a good and reliable estimate of the magnitude, severity and spatial extent of droughts. When precipitation is above the long term mean value the SPI is positive and if precipitation falls below the long term mean the SPI is negative. Unlike other drought indices, SPI is less cumbersome to use because it only requires a single input data series of long term precipitation (Smakhtin and Hughes, 2004). Because it is based on normalised data, the SPI is spatially invariant and droughts can be assessed in different regions (Guttman, 1998). The index is calculated as follows:

$$SPI = \frac{x_i - \bar{x}}{\sigma} \tag{6}$$

where, x_i is the precipitation of the selected period during the year i, $\bar{x}$ is the long term mean precipitation and σ is standard deviation for the selected period.

2.3.2. SPEI

SPEI is calculated based on the non-exceedance probability of the differences between precipitation and potential evapotranspiration, adjusted using a three-parameter log-logistic distribution which accounts for common negative values (Středová et al., 2011; Vicente-Serrano et al., 2010). SPEI uses a three-parameter distribution to capture the deficit values since it is most likely that in arid and semi-arid areas the moisture deficit can be negative. For two-parameter distributions as used in SPI, the variable x has a lower boundary of zero ($0 > x < \infty$) meaning that x can only take positive values while for the three-parameter distributions used in SPEI, x can take values in the range ($\gamma > x < \infty$) implying that x can also take negative values; γ is the parameter of origin of the distribution (Vicente-Serrano et al., 2010). Therefore the Log-logistic distribution was recommended for SPEI since it provides a better fit for the extreme negative values (Hernandez and Venkatesh Uddameri, 2014). The SPEI is obtained by normalizing the water balance into the Log-logistic probability distribution. For this study PET is estimated by the Thornthwaite method ((Thornthwaite, 1948). The difference (D_i) between precipitation (P) and PET for the month (i) is given in equation (7).

$$D_i = P_i - PET_i \tag{7}$$

The calculated D values are aggregated at different time scales as follows:

$$D_n^k = \sum_{i-0}^{k-1} P_{n-1} - (PET)_{n-1} \tag{8}$$

where k is the timescale (months) of the aggregation and n is the calculation month.

The probability density function of a Log-logistic distribution is given as:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left(1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right)^{-2} \tag{9}$$

where α, β and γ are scale, shape and origin parameters respectively for $\gamma > D < \infty$. The probability distribution function for the D series is then given as:

$$f(x) = [1 + (\alpha/x - y)^{\beta}]^{-1} \tag{10}$$

With f(x) the SPEI can be obtained as the standardised values of $F(x)$ according to the method of Abramowitz et al. (1965):

$$\text{Where } SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{11}$$

and

$$W = \sqrt{-2\ln(P)} \text{ for } P \le 0.5 \tag{12}$$

P is the probability of exceeding a determined D_i value and is given as $P = 1 - f(x)$ while the constants are:

$C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

Since SPEI is a standardised variable it can be used to compare droughts over different spatial and temporal scales. Just like the SPI, continuously negative SPEI values define a drought period based on intensity, severity, magnitude and duration (Byakatoda et al., 2016).

2.3.3. Drought identification

The characterisation of droughts for both SPI and SPEI is based on the SPI scale (McKee et al., 1993). The SPI scale is used since the computation of both indices is based on the same principles. This study places emphasis on moderate to extreme droughts and the SPI/SPEI index scale is given as, extreme drought ($\le$-2), severe drought (-2 to -1.5) and moderate drought (-1.5 to -1). It should be noted that a drought ends when the SPI/SPEI approaches zero and progresses into a positive value. For this study, the duration of the drought is considered as the number of months for which the drought has occurred while the magnitude of the indices indicates the severity of the drought. The comparison of SPI and SPEI, that is if both indices portray the same pattern (irrespective of the magnitude), is assessed using the Pearson correlation coefficient, r, which measures the strength of the statistical relationship between the SPI and SPEI. This coefficient establishes whether a linear relationship exists between the indices at the 95% confidence. The relationship coefficient (R) takes values between $+1$ and -1 where; $+1$: perfect positive relationship, 0: no relationship and -1: perfect negative relationship. The magnitude of the correlation shows the strength of the relationship and an R value $\ge$ 0.5 is deemed to be a strong correlation (Taylor, 1990). R is calculated as follows:

$$R_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \tag{13}$$

Where: n = number of observations, and for this study x and y represent the SPI and SPEI values respectively.

3. Results and discussion

To demonstrate the temporal variation of drought at different time scales (3, 6 and 12 months) in the Kafue, the SPIs and SPEIs for the different sub-basins were generated and presented in Fig. 3a–b. In general, and for all the sub-basins, both indices show the same pattern of variability for each timescale but they differ in the duration and magnitude of the drought. Variability in the droughts can be attributed to the fact that the sub-basin experiences high natural variability in climate which is characteristic of the southern African region. Also, the frequency of occurrence of the droughts is higher for the shorter timescale compared to the longer timescales; it takes a shorter time (at most 1 month) of prevailing water deficiency for a meteorological drought, thus the high variability of droughts. On the other hand, a longer period of water deficit accumulation or depletion of water storage in rivers and reservoirs is required for a hydrological drought to occur. Hence, the meteorological droughts (1 month timescale) show the highest frequency of occurrence followed by agricultural droughts (3–6 month timescale) and lastly the hydrological droughts (12 month time scale). However, at the higher timescales the drought lasts longer and the magnitude increases.

Given that it takes up to 6 months for most crops to be fully developed, a water deficiency accumulation of at least 3 months, during the growing season, will adversely impact crop yields, thus developing into an agricultural drought. Since drought develops over time, it can be assumed that the extended period of drought at longer timescales may be a result of the after-effects of accumulation of antecedent water scarcity over time and this situation may be amplified with persistent and continuous periods of no rainfall. In addition, a drought can occur if there is a shift in seasonal rainfall such that the rains are delayed thus causing impairment on activities that normally depend on the onset of a rainfall event.

Apparent differences during some years and irrespective of the

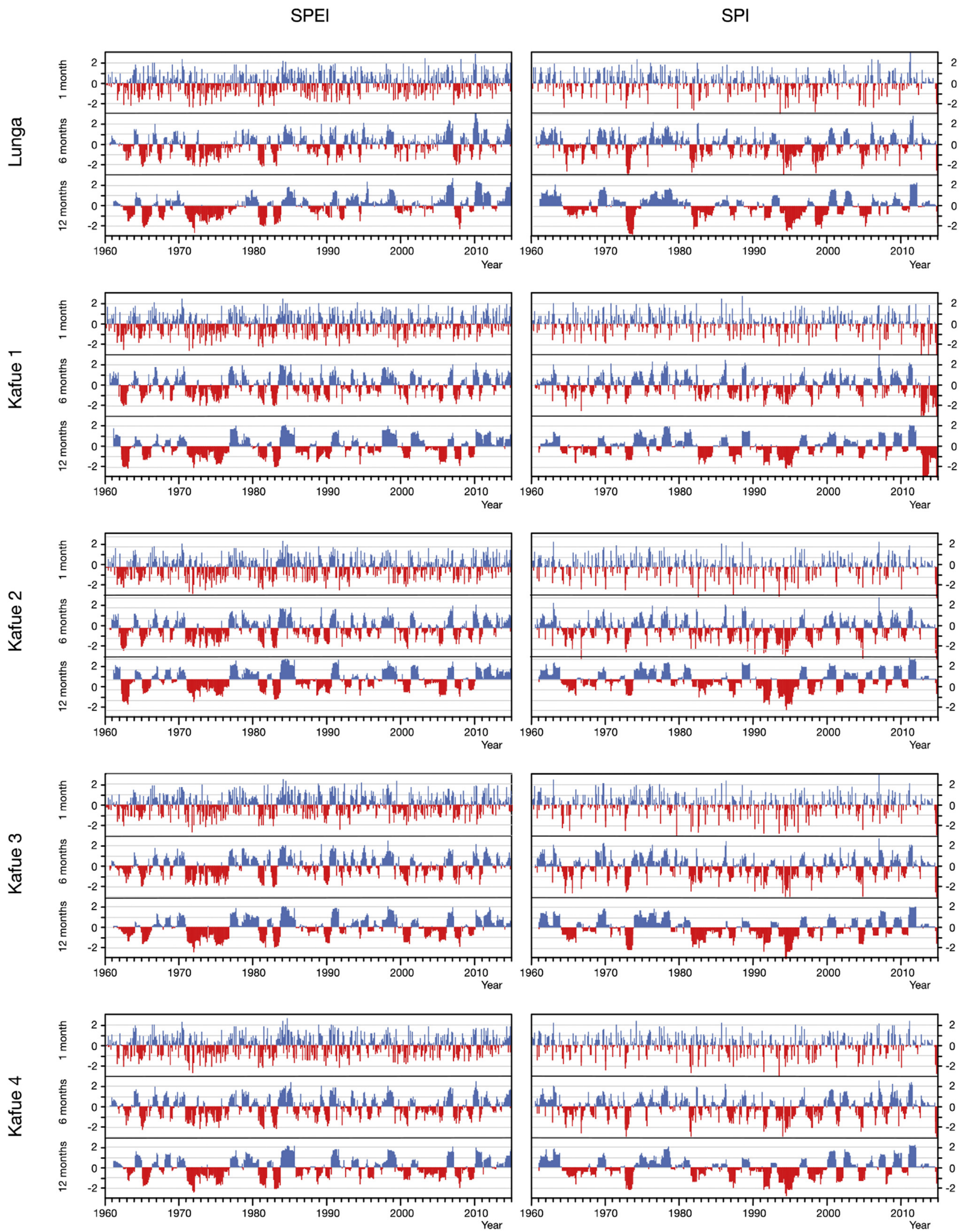

Fig. 3a. SPEI and SPI at different timescales for the Kasaka, Lufwanyama, Luswishi and Nanzhila sub-basins of the Kafue.

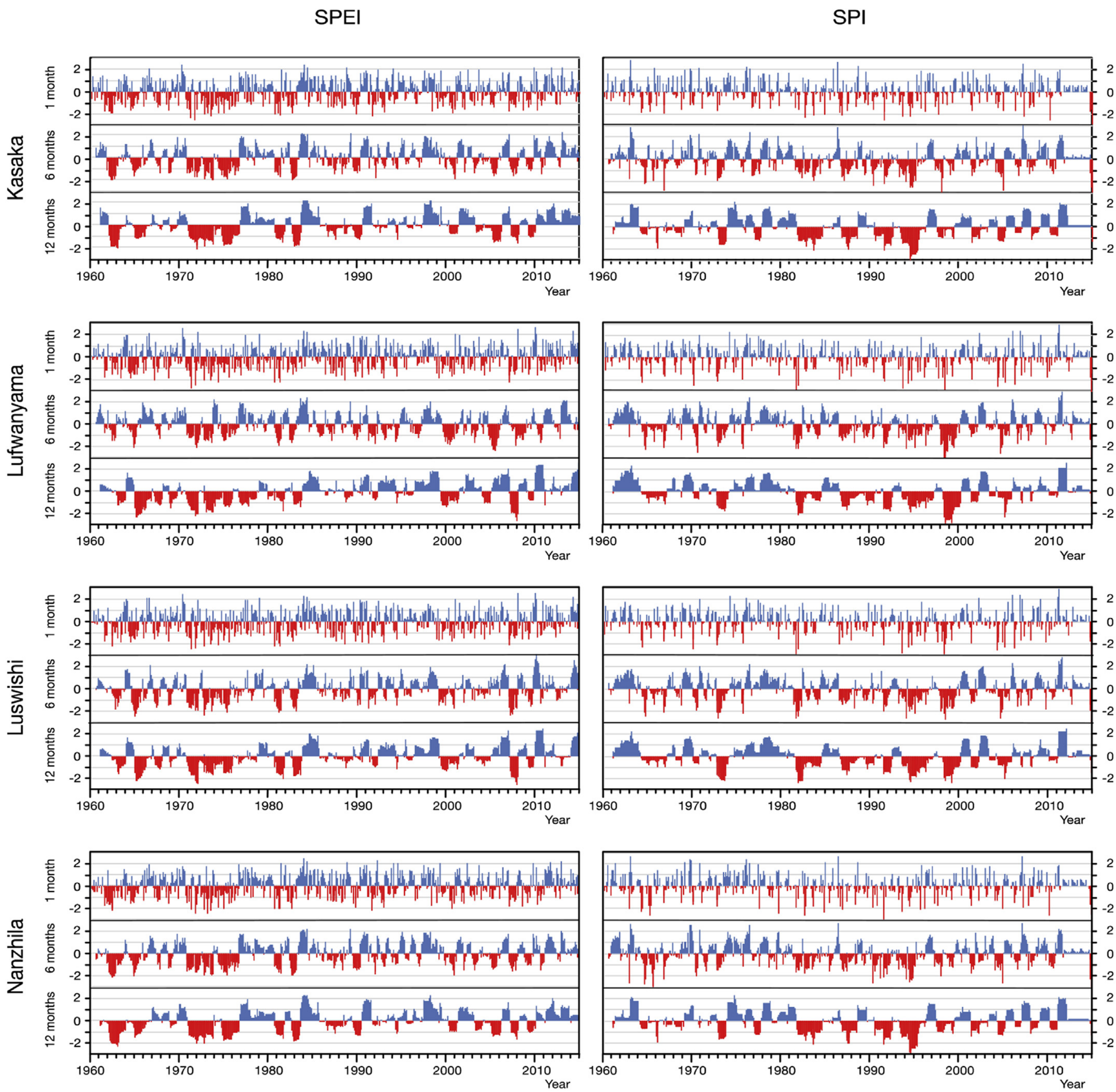

Fig. 3b. SPEI and SPI at different timescales for the Lunga and Kafue1 to Kafue 4 sub-basins of the Kafue.

timescale were noted between the SPI and SPEI. Longer droughts occurred under SPEI; here the duration of the drought is extended as the counts of droughts increase in the yearly time series. For some of the years that were already experiencing drought conditions under SPI, the magnitude of the drought was amplified when detected by the SPEI. That SPEI produces droughts of increased magnitude can be explained by the fact that evapotranspiration imposes a demand on the available water and the impact is felt the most under conditions of water scarcity.

Table 2 shows the number of droughts per year, including the drought categories for the Lunga sub-basin. For the period under observation (1960–2015) the most common agricultural and hydrological droughts were observed during the years 1964–1965, 1967, 1971–1973, 1981–1983, 1987, 1990–1992, 2001 and 2008, the same applies to all the other sub-basins of the Kafue. Fig. 4 shows that SPEI identified more droughts than SPI under the moderate to severe drought categories across all sub-basins and for all time scales. The results show that even though reduced precipitation is the major driver of droughts, the effect of temperature through evaporative water demand has a role to play in the determination of droughts. Considering rainfall alone, more droughts are classified as extreme compared to when including PET. Overall Fig. 4 shows that the highest number of droughts under 6 and 12 monthly timescales occurred in the Nanzhila sub-basin which is located in the southernmost part of the Kafue basin.

Correlations between SPI and SPEI for the different sub-basins of the Kafue and under different timescales are depicted in Fig. 5. Statistically significant positive correlations ($R > 0.5$) exist between the two indices. Under climatic conditions with low inter-annual variability in temperature compared to the variability in rainfall, the results imply that both indices will predominantly respond more to the variations in precipitation suggesting that precipitation is the major driver of water

Table 2
Drought years and drought categories of SPI and SPEI at different time scales in the Lunga sub-basin.

	SPI 1				SPEI 1				SPI 3				SPEI 3				SPI 6				SPEI 6				SPI 12				SPEI 12			
Year	Extreme	Severe	Moderate	Σ	Extreme	Severe	Moderate	Σ	Extreme	Severe	Moderate	Σ	Extreme	Severe	Moderate	Σ	Extreme	Severe	Moderate	Σ	Extreme	Severe	Moderate	Σ	Extreme	Severe	Moderate	Σ	Extreme	Severe	Moderate	Σ
1962	-	-	-	-	1	1	1	3	-	-	-	-	-	3	-	3	-	-	-	-	-	2	-	2	-	-	-	-	-	-	-	-
1963	-	-	-	-	1	-	2	3	-	-	-	-	-	-	3	3	-	-	-	-	-	-	4	4	-	-	-	-	-	1	7	8
1964	1	1	-	2	-	3	3	6	1	1	1	3	1	1	4	6	1	1	2	4	1	1	3	5	-	-	-	-	-	-	-	-
1965	-	-	-	-	-	1	1	2	-	-	3	3	-	1	2	3	-	-	-	-	1	3	3	7	-	-	-	-	2	7	3	12
1966	-	-	3	3	-	-	-	-	-	3		3	-	-	-	-	-	3	-	3	-	-	-	-	-	-	-	-	-	-	-	-
1967	-	-	-	-	-	-	-	-	-	-	-	-	1	1	4	6	-	-	-	-	-	3	3	6	-	-	-	-	-	-	9	9
1971	-	-	-		2	1	1	4	-	-	-	-	1	3	3	7	-	-	-	-	1	4	5	10	-	-	-	-	1	7	2	10
1972	-	2	-	2	1	1	1	3	-	-	-	-	1	1	1	3	-	-	-	-	2	1		3	-	-	-	-	2	-	2	4
1973	-	1	2	3	1	1	3	5	2	1	1	4	1	2	3	6	-	-	-	-	1	2	6	9	9	3	-	12	-	3	6	9
1974	-	-	-	-	-	-	-	-	-	-	-	-	-	-	5	5	-	-	-	-	-	1	5	6	-	-	-		-	1	9	10
1975	-	-	-	-	-	1	2	3	-	-	-	-	-	3	1	4	1	-	1	2	-	2	4	6	-	-	-		-	-	10	10
1981	-	1		1	2	1	3	6	1	1	1	3	2	6	1	9	1	1	1	3	3	5	1	9	-	-	-	-	1	9	2	12
1982	-	1	1	2	-	-	2	2	-	2	1	3	-	-	-	-	2	4		6	-	-	-	-	7	-	2	9	-	-	2	2
1983	-	-	-	-	1	-	2	3	1	-	2	3	1	2	2	5	-	1	3	4	1	5	-	6	-	-	-	-	-	8	3	11
1987	-	-	-	-	-	-	3	3	-	-	4	4	-	1	3	4	-	-	5	5	-	-	-	-	-	-	-	-	-	-	7	7
1990	-	-	-	-	-	2	2	4	-	-	-	-	1	-	2	3	-	-	-	-	1	-	4	5	-	-	-	-	-	-	-	-
1991	-	-	-	-	-	2	1	3	-	-	-	-	-	1	1	2	-	-	-	-	-	1	1	2	-	-	-	-	-	-	-	-
1992	-	-	-	-	-	1	1	2	-	1	2	3	1	1		2	-	1	5	6	-	1	5	6	-	-	10	10	-	-	-	-
1993	-	-	-	-	1	-	3	4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
1994	-	2	-	2	1	-	-	1	1	2	1	4	-	-	-	-	1	2	1	4	-	-	-	-	-	-	-	-	-	-	-	-
1995	-	1	-	1	3	-	-	3	2	1	2	5	-	-	-	-	3	4	2	9	-	1	1	2	10	2	-	12	-	-	-	-
1996	-	-	-	-	-	-	-	-	-	1	3	4	-	-	-	-	-	-	6	6	-	-	-	-	-	1	10	11	-	-	-	-
1999	2		2	4	-	-	-	-	1	3	3	7	-	-	-	-	2	6	2	10	-	-	-	-	1	10	1	12	-	-	-	-
2000	-	-	-	-	-	-	-	-	-	-	-	0	-	1	2	3	-	1	2	3	-	-	-	-	1	1	1	3	-	-	-	-
2001	-	-	-	-	-	3	1	4	-	-	-	0	-	3	3	6	-	-	-	-	-	3	-	3	-	-	-	-	-	-	-	-
2003	-	-	-	-	-	1	2	3	-	-	-	0	-	-	3	3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2005	2	1	1	4	-	-	-	-	2	1	2	5	-	-	-	-	2	1	2	5	-	-	-	-	-	-	-	-	-	-	-	-
2006	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	3	3	-	-	-	-	-	-	-	-	-	-	-	-
2007	1	1	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2008	-	-	-	-	1	1	4	6	-	-	-	-	-	-	-	-	-	-	-	-	1	5	3	9	-	-	-	-	1	2	6	9
2011	-	-	-	-	-	1	2	3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2013	-	-	-	-	-	-	3	3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2015	2	1	-	3	-	-	-	-	2	1	-	3	-	-	-	-	2	1		3	-	-	-	-	-	-	-	-	-	-	-	-
Sum	8	12	9	29	15	21	43	79	13	18	26	57	10	30	43	83	15	26	35	76	12	40	48	100	28	17	24	69	7	38	68	113

availability.

The differences observed between SPI and SPEI for some months suggest that inclusion of potential evapotranspiration is important especially given that evaporative water demand is quite important in determining water availability and in view of it being a major component of the hydrological water balance. Moreover, water availability is also judged from available soil moisture, of which potential evapotranspiration provides a reasonable indication of the soil water losses.

4. Conclusion

This study compared SPI and SPEI in determining droughts. SPI is a precipitation-based index while SPEI makes use of a water balance based on the difference between precipitation and evapotranspiration. Both indices identified the temporal variability of droughts and were able to identify different types of droughts as indicated by the different timescales. Compared to SPI, SPEI captured more severe and moderate droughts under the study period of 1906–2015. Although not very apparent, the SPEI droughts occurred with longer duration and increased magnitude. This arises from the fact that temperature enhances the rates of potential evapotranspiration, consequently increasing the evaporative water demand (Dubrovsky et al., 2008) and therefore causing a water deficit. However, when considering precipitation alone, SPI identified more extreme droughts compared to SPEI. Correlation analysis between SPI and SPEI clearly indicates that precipitation is the major driver of drought. The results show that SPEI and SPI have lower correlation for shorter timescales (meteorological followed by agricultural droughts); that is, the indices pick up different signatures. However, the inclusion of potential evapotranspiration becomes important at the longer timescales where the correlations are stronger. Already it is largely accepted that precipitation plays a larger role in determining droughts and that evapotranspiration has considerable

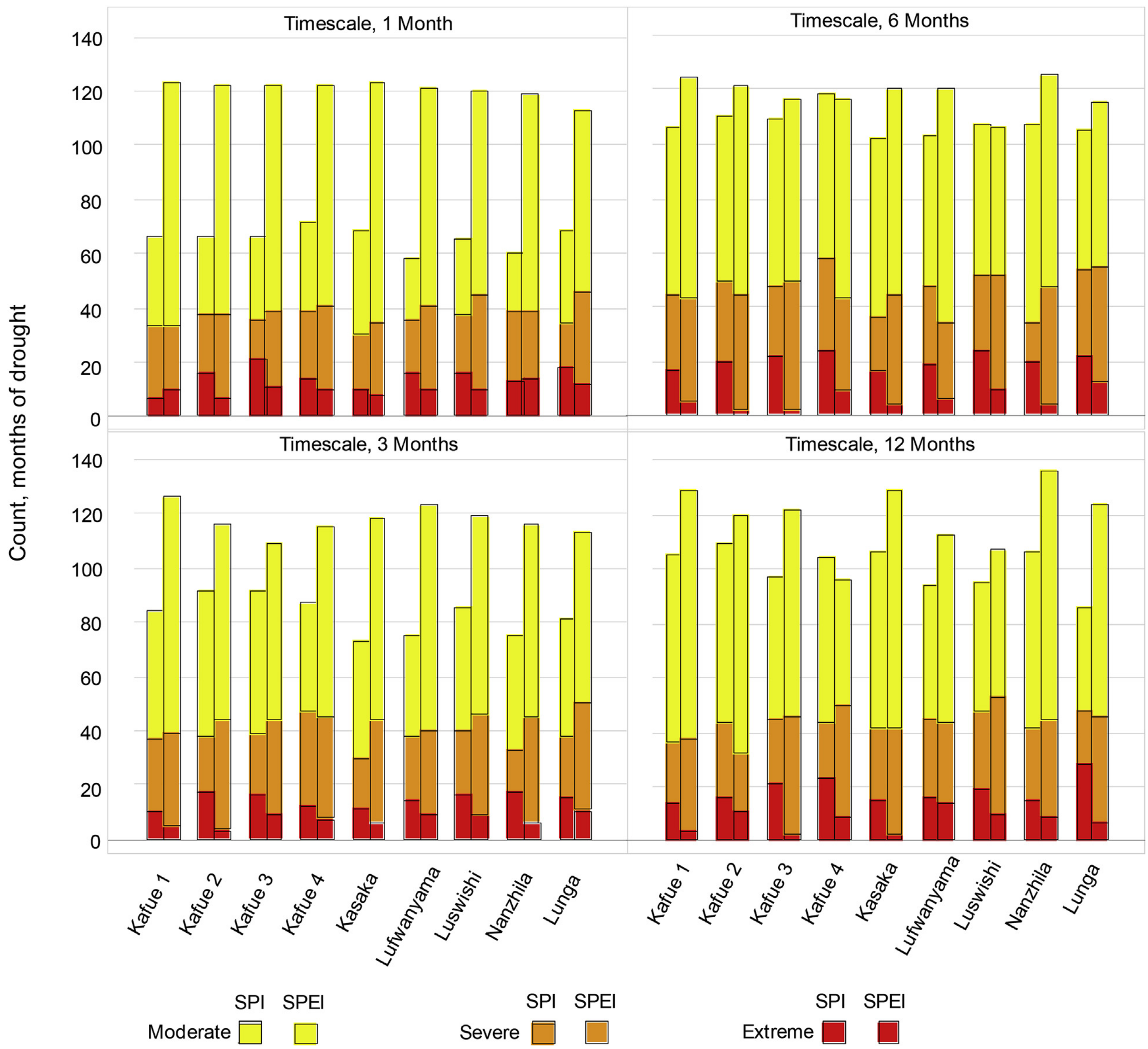

Fig. 4. Number of drought events (1960–2015) at different time scales for the Kafue sub-basins. Left columns show SPI and right columns SPEI.

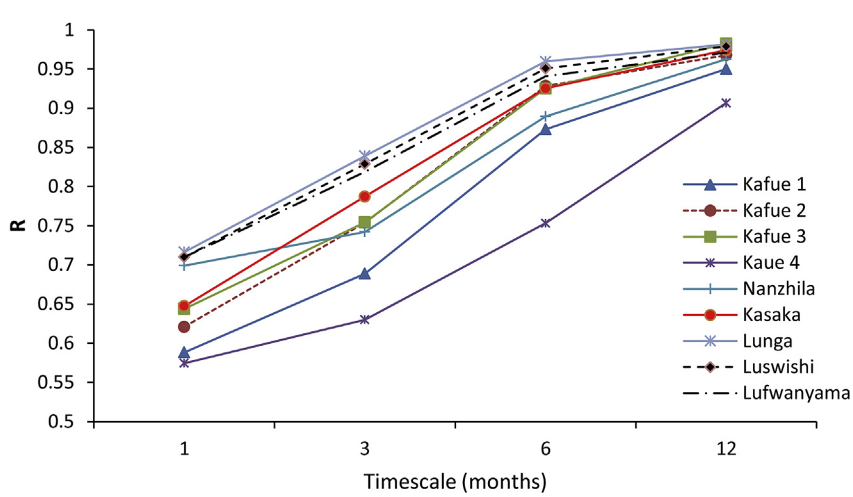

Fig. 5. Correlation between SPI and SPEI at different time scales for the Kafue sub-basins.

spatiotemporal effects on soil moisture availability and consequently on agricultural droughts (Hao et al., 2018). It is because of this that SPEI should be used in water resources planning in the face of drought. Hence, we suggest that SPI must be used with caution while at the same time SPEI can be useful especially under conditions where the effects of evapotranspiration are felt the most. Nonetheless, it should be noted that this study aimed at establishing the difference between the two indices and since no validation was performed on the results, conclusion cannot be drawn on which of the two is the better indicator of drought.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.pce.2018.07.001.

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