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DROUGHT INDICES AND THEIR APPLICATION TO EAST AFRICA

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ABSTRACT

This study analysed and modified (where necessary) the properties of three drought indices: the Palmer drought severity index (PDSI), the Bhalme–Mooley index (BMI) and the standardized precipitation index (SPI). We modified the original PDSI's recursive formula, potential runoff, and Z index, which produced more realistic results than the original PDSI (designed for the USA) for East Africa. We improved the SPI by first using a plotting position formula designed for the Pearson type III (P3) distribution to transform the 'smoothed' precipitation data into non-exceedance probabilities, which we then transformed into standard P3 variates by the regional flood index method. The modified SPI depicted East Africa's drought conditions more accurately than the original SPI. Using the three indices and East Africa as a case example, we identified eight assessment criteria to determine the most appropriate index for detecting drought events on a regional basis. BMI produced results that are highly correlated to those of the modified PDSI, which suggested that precipitation alone could explain most of the variability of East African droughts. Furthermore, among the three indices, SPI is more appropriate for monitoring East African droughts because it is more easily adapted to the local climate, has modest data requirements, can be computed at almost any time scale, provides relatively consistent power spectra spatially, has no theoretical upper or lower bounds, and is easy to interpret. Copyright © 2003 Royal Meteorological Society.

KEY WORDS: East Africa; drought indices; Palmer drought severity index; Bhalme–Mooley index; standardized precipitation index; precipitation

1. INTRODUCTION

Drought indices designed to provide a concise overall picture of droughts are often derived from massive amounts of hydroclimatic data and are used for making decisions on water resources management and water allocations for mitigating the impact of droughts. Ideally, the use of quantitative drought indices for drought management reduces the subjective preferences of decision makers. A variety of drought definitions have been used in the past (e.g. Gibbs, 1975; Wilhite and Glantz, 1987), and Table I shows some drought indices that are currently in use or have been used in the past.

1.1. Research objective

The primary objective of this study is to analyse the properties of three popular drought indices and modify them where necessary to increase their general effectiveness and dependability in detecting droughts. Using the three indices and East Africa as a case example, the second objective is to identify assessment criteria for determining the most appropriate drought index for detecting the initiation, evolution, and termination of droughts on a regional basis. From Table I, the indices chosen for this study were

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Table I. The characteristics of some present and past drought indices

Index and its developer	Input data[a]	Time scale	Brief description
PDSI: Palmer (1965)	P, T, CPI	Weekly, biweekly, monthly	The PDSI is a soil moisture algorithm calibrated for relatively homogeneous regions. It is based on moisture inflow, outflow and storage. Many US government agencies and states still rely on the PDSI to trigger drought relief programs
Crop moisture index: Palmer (1968)	P, T, ET, L, RO	Weekly	A PDSI derivative, which reflects moisture supply in the short term across major crop-producing regions
SPI: McKee *et al.* (1993)	P	Multiples of months	An index based on the probability of precipitation for any time scale
Surface water supply index (SWSI): Shafer and Dezman (1982); Garen (1993)	P, sn, RO, reservoir storage	Monthly	The SWSI is based on probability, similar to the SPI, but it also considers the snow pack, runoff, and reservoir storage
Reclamation drought index (RDI): Bureau of Reclamation (USA)	P	Monthly	RDI is calculated on the river basin scale. Since the index is unique to each river basin, interbasin comparison is not possible
BMI: Bhalme and Mooley (1979)	P	Monthly	The BMI models the percentage departure of P from the long-term averages using an algorithm similar to that of the PDSI
Deciles: first promoted by the Australian drought authorities, who currently use it	P	Monthly	The decile method groups monthly precipitation occurrences into deciles. By definition 'much lower than' normal precipitation cannot occur more often than 20% of the time
Precipitation anomaly classification (PAC): Janowiak *et al.* (1986)	P	Monthly or yearly	The PAC is an improvement of the Australian 'decile' method of drought classification
National rainfall index (NRI): Gommes and Petrassi (1994)	P	Monthly	The NRI patterns abnormalities of precipitation on a continental scale
Percentage of normal (PN)	P	Monthly	PN is obtained by dividing P with the normal value. It is a simple calculation well suited to the needs of TV weather people and general audiences

[a] P: precipitation; T: temperature; ET: evapotranspiration; L: soil moisture; RO: runoff; sn: snowpack.

the Palmer drought severity index (PDSI), Bhalme–Mooley index (BMI) and the standardized precipitation index (SPI), partly because they are non-basin-specific indices that can theoretically be used for drought comparisons in regions of different climates. The theoretical background of these indices is examined first.

2. PDSI

The PDSI (Palmer, 1965) is probably still one of the most complex drought indices in use today (Titlow, 1987), and it is also one of the few that allows a direct comparison of index values between different climatological regions. It is probably the most widely used drought index in the USA, where it is computed weekly for 344 climatic divisions of the country and published in *The Weekly Weather and Crop Bulletin* of the US Department of Commerce, National Oceanic and Atmospheric Administration (NOAA) and the US Department of Agriculture (USDA).

2.1. PDSI algorithm

The PDSI analyses either a weekly or monthly water budget, and assumes that evapotranspiration (ET) occurs close to the potential monthly ET (PE) until a certain amount of the available water is depleted, after which the actual ET is less than PE. The PDSI uses the following equations to compute the moisture transfer between soil layers:

$$L_s = \min\{S_s, (\mathrm{PE} - P)\} \quad P \le \mathrm{PE} \tag{1}$$

$$L_u = \frac{[(\mathrm{PE} - P) - L_s]S_u}{\mathrm{AWC}} \quad L_u \le S_u,\ P \le \mathrm{PE} \tag{2}$$

where P is the precipitation, L_s and L_u (S_s and S_u) are the moisture loss (available soil moisture stored) in the upper or surface and underlying layer(s) respectively at the start of the month, and AWC is the combined available field capacity of all soil layers. Palmer (1965) assumed that no runoff occurs until both layers reach field capacity. He estimated PE by Thornthwaite's (1948) method, which has an approximate daily absolute error of 35%, but PE could be in error by over 100% on some individual days. As the time scale being considered increases to about 2 weeks or longer, however, the error decreases to about 10 to 15%, which Palmer (1965) suggested as being acceptable for the climatological analysis of moisture requirements.

Palmer (1965) also computed the potential recharge (PR) that brings the soil to field capacity, the potential loss (PL) of soil moisture to ET during dry periods, and the potential runoff (PRO):

$$\mathrm{PR} = \mathrm{AWC} - (S_s + S_u) \tag{3}$$

$$\mathrm{PL} = \mathrm{PL}_s + \mathrm{PL}_u \tag{4}$$

where

$$\mathrm{PL}_s = \min(\mathrm{PE}, S_s) \tag{5}$$

$$\mathrm{PL}_u = (\mathrm{PE} - \mathrm{PL}_s)\frac{S_u}{\mathrm{AWC}} \quad \mathrm{PL}_u \le S_u \tag{6}$$

$$\mathrm{PRO} = \mathrm{AWC} - \mathrm{PR} = S_s + S_u \tag{7}$$

From PE, PR, PL and PRO, there are four coefficients related to the climate of the area:

$$\lambda_{1,j} = \frac{\overline{\mathrm{ET}}_j}{\overline{\mathrm{PE}}_j} \tag{8}$$

$$\lambda_{2,j} = \frac{\overline{L}_j}{\overline{\mathrm{PL}}_j} \tag{9}$$

$$\lambda_{3,j} = \frac{\overline{R}_j}{\overline{\mathrm{PR}}_j} \tag{10}$$

$$\lambda_{4,j} = \frac{\overline{\mathrm{RO}}_j}{\overline{\mathrm{PRO}}_j} \tag{11}$$

where $\overline{\mathrm{ET}}_j$, $\overline{L}_j$, $\overline{R}_j$, and $\overline{\mathrm{RO}}_j$ are monthly mean evapotranspiration, moisture loss, water recharge, and runoff respectively, and $j = 1, 2, \ldots, 12$. The overbars signify that the variables are average values of month j. From these variables, Palmer (1965) computed the 'climatologically appropriate for existing conditions' (CAFEC) precipitation $\hat{P}_{w,j}$ and the departure d of the monthly precipitation from $\hat{P}_{w,j}$ (where w refers to the year):

$$\hat{P}_{w,j} = \lambda_{1,j}\mathrm{PE}_{w,j} - \lambda_{2,j}\mathrm{PL}_{w,j} + \lambda_{3,j}\mathrm{PR}_{w,j} + \lambda_{4,j}\mathrm{PRO}_{w,j} \tag{12}$$

$$d_{w,j} = P_{w,j} - \hat{P}_{w,j} \tag{13}$$

To compare $d_{w,j}$ among regions, Palmer (1965) introduced a moisture anomaly index $Z_{w,j}$ that signifies the departure of the monthly weather from the 'climatically normal' conditions for j:

$$Z_{w,j} = K_j d_{w,j} \tag{14}$$

where

$$K_j = 1.5\log_{10}\left(\frac{T_j + 2.8}{\overline{D}_j}\right) + 0.50 \tag{15}$$

$\overline{D}_j$ is the monthly average of $d_{w,j}$, and T_j is the ratio of 'moisture demand' to 'moisture supply':

$$T_j = \frac{\mathrm{PE}_j + R_j + \mathrm{RO}_j}{P_j + L_j} \tag{16}$$

Weighting $d_{w,j}$ with K_j in Equation (14) facilitated the moisture deficit comparison among different areas and for different months. Equations (15) and (16) were derived using data from nine areas in the USA. According to Alley (1984), Palmer (1965) had difficulty deriving the unusually complex form of Equations (15) and (16).

By plotting Z versus duration for the worst drought episodes in his study area, Palmer (1965) obtained a linear relationship from which he derived the drought severity equation:

$$X_j = 0.897X_{j-1} + 0.333Z_j \tag{17}$$

To use Equation (17), one needs to identify the starting month of a wet or a dry spell by keeping track of three pseudo-indices *X1, X2*, and *X3*:

$$\left.\begin{aligned} X1_j &= 0.897X1_{j-1} + 0.333Z_i \\ X2_j &= 0.897X2_{j-1} + 0.333Z_i \\ X3_j &= 0.897X3_{j-1} + 0.333Z_i \end{aligned}\right\} \tag{18}$$

which respectively represent conditions of 'wet spell becoming established', 'dry spell becoming established' and 'wet or dry spell that has become established'. *X1* is restricted to non-negative values and *X2* is the reverse. The values of *X1* and *X2* are set to zero when Equation (18) violates these restrictions. Palmer (1965) considered a drought to be established when $X2 \leq -1.0$, and a wet spell is established when $X1 \geq 1.0$. A drought is considered to have certainly ended when the index reaches the 'near normal' category, which lies between -0.5 and $+0.5$, when *X3* returns to zero. The decision as to which of the three indices becomes X (e.g. set to non-zero index) depends on whether the dry/wet spells are incipient, established, or ended. However, conflicting cases can arise and the appropriate X to use is not always obvious. To select a final value of X, Palmer (1965) devised a set of complicated operating rules that relied on computing *X1*, *X2*, and *X3* over several months and then backtracking until a month with a known X was reached (Alley, 1984): (i) from an established drought, assign $X = X1$ until $X1 = 0$; (ii) then assign $X = X2$ until $X2 = 0$; (iii) repeat steps (i) and (ii) until a month is reached that already has an X value assigned to it; and (iv) if the pseudo-indices are such that the above rules cannot be conclusively used to select the X, select the PDSI as *X1* or *X2*, whichever has the largest absolute value, whenever *X3* equals zero.

Because of its complexity, it is common for the time series of PDSI to exhibit large sudden changes. Alley (1984), Titlow (1987), Heddinghaus and Sabol (1991), Guttman (1998) and others have noted the shortcomings of the PDSI. These include: (1) representative values of soil storage capacities are difficult to estimate accurately, and two soil layers may not be representative enough for a location; (2) assuming runoff cannot occur unless soil moisture is at field capacity is not necessarily true, and Palmer's model does not account for the delay between the generation of excess water and the appearance of runoff; (3) there is no justification to equate the potential precipitation with AWC; (4) PE estimated by the Thornthwaite method depends only on latitude, which means two locations of similar latitude and monthly temperatures would have the same PE even though they could be located on different continents with different altitudes, climate, etc.; (5) the abrupt switching among *X1*, *X2* and *X3* as the value of the PDSI has prevented the introduction of stochastic elements into the index.

Furthermore, the PDSI is a regional index developed in the USA, and so it may not work well elsewhere. Over the last three decades, however, little has been changed in the PDSI algorithm. Bhalme and Mooley (1979) showed that the PDSI failed to describe the drought conditions in tropical India realistically and attempted to modify its coefficients. Cancelliere *et al.* (1996), however, found the PDSI to be applicable in the Mediterranean region. Based on the PDSI, Briffa *et al.* (1994) analysed the surface moisture variability across Europe, and Jones *et al.* (1996) reviewed the moisture availability of Europe simulated by the Hadley Centre general circulation model. Scian and Donnari (1997) examined the PDSI in the semi-arid Pampas region of Argentina; they used pan evaporation instead of the Thornthwaite method. Heddinghaus and Sabol (1991) adjusted the rules for appropriating a value to X when there was no knowledge as to whether a wet or a dry spell had been established. Wells (2002) developed self-calibrating PDSI software to replace the empirical constants of PDSI at any location automatically. Herein, we suggest some modifications to the PDSI in an attempt to make it more versatile and applicable outside of the USA.

2.2. *Suggested improvements to the PDSI*

To obtain the PRO, Palmer (1965) assumed the potential precipitation as equivalent to AWC, but he was uncomfortable about this assumption. The complication of finding PRO could be avoided by using an alternative method that does not require potential precipitation as an input, for we can safely assume that $\mathrm{PRO}_{w,j}$ cannot exceed the precipitation of that month j. The upper limit would be when the soil is saturated and the ET losses are negligible, and so $\mathrm{PRO}_{w,j}$ would be equivalent to the month's rainfall, i.e.

$$\mathrm{PRO}_{w,j} = P_{w,j} \tag{19}$$

The coefficient $\lambda_{4,j}$ of the actual runoff in relation to PRO is still given by Equation (11). Hence, the CAFEC precipitation (Equation (12)) could be modified as

$$\hat{P}_{w,j} = \lambda_{1,j}\mathrm{PE}_{w,j} - \lambda_{2,j}\mathrm{PL}_{w,j} + \lambda_{3,j}\mathrm{PR}_{w,j} + \lambda_{4,j}\mathrm{P}_{w,j} \tag{20}$$

A second improvement is that instead of forcing a functional relationship on the Z index empirically (e.g. Equations (14)–(16)), the departures can be normalized in a way similar to that of Bhalme and Mooley (1980) to facilitate a temporal and spatial comparison:

$$Z_{w,j} = 100\frac{d_{w,j} - \mu_j}{\sigma_j} \tag{21}$$

where μ_j and σ_j are the monthly departure means and standard deviations respectively.

Third, we re-derive Equation (17) given that it has constants that should vary with location because the progression of droughts varies from place to place. Even though researchers such as Scian and Donnari (1997) and Cancelliere *et al.* (1996) used the original equation in areas other than the USA with some success, we feel that they could have done better if they had changed the coefficients of Equation (17) to reflect the local conditions better. The plot of Z for the worst droughts of various durations often gives a straight line (Palmer, 1965). In the hypothetical example (Figure 1), where the solid line represents extreme drought with X arbitrarily fixed at -4, the driest 38 month period had a cumulative $Z = -57$. The vertical distance

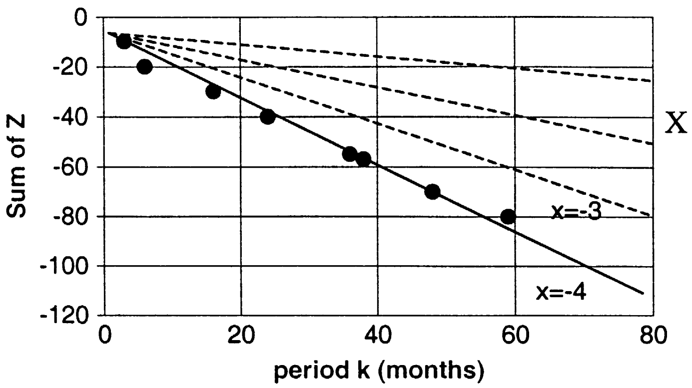

Figure 1. Plots of some hypothetical, cumulative Z versus period k (months) for four levels of drought episodes indicated by the drought severity parameter X

between this solid line and the t-axis at $Z = 0$ is divided into four equal lengths by drawing three dashed lines representing severe, moderate and mild droughts. It can be shown that the equation of the extreme drought line is given by

$$X_k = \frac{\sum_{t=1}^{k} Z_t}{a + kb} \tag{22a}$$

where X_k is the drought intensity of the kth month, $\sum_{t=1}^{k} Z_t$ is the accumulative moisture index over duration k, $a = -c/4$ and $b = -m/4$, where c and m are the intercept and slope respectively of the extreme drought line, since for this drought line, $X_k = -4$, e.g.

$$X_k = \frac{4\sum_{t=1}^{k} Z_t}{10.12 + 1.22k} \tag{22b}$$

Equations (22a) and (22b) provide only a partial drought severity expression because they are based on the cumulative sum of Z. As Palmer (1965) and Bhalme and Mooley (1980) pointed out, the cumulative procedure of accounting for the dry period duration can be misleading because X_k in Equations (22a) and (22b) depends partly on the order of k. For example, the same Z_t could have a different contribution to the drought index depending on whether it is the second or the sixth month in the computation sequence.

To resolve this problem, it is necessary to revise Equations (22a) and (22b) such that the incremental drought intensity contribution for each successive month is independent of the month in which it occurred. For the initial month, let $X_0 = 0$. The contribution of the next month can be obtained by setting $k = 1$ in Equation (22a) to obtain

$$X_1 = \frac{Z_1}{a + b} \tag{23}$$

The change in X is

$$X_1 - X_0 = \Delta X = \frac{Z_1}{a + b} \tag{24}$$

In successive months a negative Z will be required to maintain the existing dry spell, with a required magnitude depending on the magnitude of the previous drought index X:

$$\Delta X_k = \frac{Z_k}{a+b} + \theta X_{k-1} \tag{25}$$

where

$$\Delta X_k = X_k - X_{k-1} \tag{26}$$

In Equation (25), the Z of each successive month contributes to the previous drought index on an incremental basis and is independent of k. To determine the constant θ we use Equation (22a) for $t = k - 1$ and k, with X_k and X_{k-1} kept at some constant value ϕ, such that

$$Z_k = \sum_{t=1}^{k} Z_t - \sum_{t=1}^{k-1} Z_t = b\phi \tag{27}$$

From Equations (25) and (27)

$$\theta = \frac{-b}{a+b} \tag{28}$$

From Equation (25)

$$X_k = \left(\frac{a}{a+b}\right) X_{k-1} + \frac{Z_k}{a+b} \tag{29}$$

and since $a = -c/4$ and $b = -m/4$, then

$$X_k = \left(\frac{c}{c+m}\right) X_{k-1} + \frac{-4Z_k}{c+m} \tag{30}$$

Equation (29) or (30) is the drought relationship of the PDSI used recursively to track drought conditions. In Palmer's (1965) analysis, a and b were 2.691 and 0.309 respectively. There is little basis to use these values for regions different from those of Palmer. Figure 2 illustrates the difference between the extreme drought line of Palmer (1965) and that of selected East African stations that have diverse drought progression characteristics and hence different a and b. We propose rewriting Equations (17), (29) and (30) in the general form

$$X_k = \varphi X_{k-1} + \epsilon Z_k \tag{31}$$

where $\varphi = c/(c+m)$ and $\varepsilon = -4/(c+m)$. Equation (31) is obviously a first-order autoregressive model, AR(1). However, PDSI is not a pure AR(1) process because the final value X at times shifts abruptly between pseudo-indices *X1, X2*, and *X3* according to some predefined rules. The coefficients of regression determine the magnitudes of c and m (whose relative values vary from place to place, e.g. c could be much less than m), and hence the progression of the dry or wet spell; Table II shows this, together with the values established by Palmer (1965).

In most cases, the plot of Z versus duration is almost linear, as shown by the consistently high correlation or goodness-of-fit ρ in Table II. Even though φ does not change much, all the φ values are less than the 0.897 of Palmer (1965), and ε differs by four or five times from Palmer's original ε of 0.333. Different φ and ε will produce different PDSI values. Therefore, we propose computing φ and ε for each station, for there is little basis to use the same φ and ε for all stations unless they all exhibit the same extreme drought characteristics, which is clearly not the case in East Africa. Although φ and ε are obtained from individual

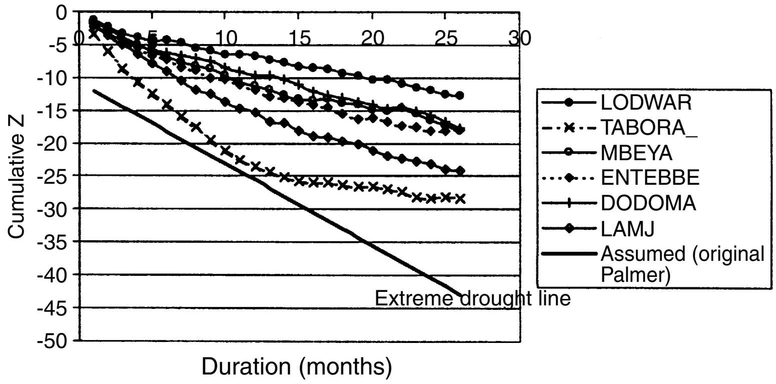

Figure 2. Plots of the most negative cumulative moisture index Z versus duration (ranging from 2 to 30 months) for the original PDSI and some selected East African stations

Table II. A comparison between the coefficients of regression (c and m) and resulting drought severity terms (φ and ε) estimated for East African stations with the original PDSI parameters. The goodness-of-fit for each station is indicated by the correlation ρ

Station name	Latitude	Longitude	Intercept c	Slope m	Correlation ρ	Equation (31) parameters	
						φ	ε
Lodwar	3.12	36	−1.899	−0.412	0.992	0.822	1.731
Mandera	3.93	42	−1.867	−0.565	0.998	0.768	1.645
Wajir	1.75	40	−1.491	−0.443	0.996	0.771	2.068
Kisumu	−0.10	35	−3.508	−0.576	0.989	0.859	0.979
Garissa	−0.47	40	−1.797	−0.435	0.993	0.805	1.792
Lamu	−2.27	41	−3.782	−0.861	0.983	0.815	0.861
Mombasa	−4.03	40	−2.728	−0.417	0.989	0.868	1.272
Kigoma	−4.88	30	−3.95	−0.812	0.991	0.830	0.84
Dodoma	−6.17	36	−2.384	−0.551	0.995	0.812	1.363
Mtwara	−10.27	40	−4.739	−0.642	0.971	0.881	0.743
Original PDSI			**−10.764**	**−1.236**	**–**	**0.897**	**0.333**

extreme-drought lines (Figure 2), the resulting PDSI time series should theoretically be comparable across stations because they are all calibrated against the driest conditions possible at each individual location.

3. BMI

Bhalme and Mooley (1980) developed the BMI for assessing the drought intensity using precipitation only. The computational details of the BMI and the PDSI are generally similar, with just a few differences. Bhalme and Mooley substituted the moisture index Z in Palmer's algorithm with a simpler monthly rain index M computed from the rainfall data only. Furthermore, the BMI does not involve the simultaneous tracking of pseudo indices of dry, wet, or unestablished spells, which could be confusing. To obtain the BMI, first compute the monthly rainfall mean μ and standard deviation σ, then obtain the moisture index M as:

$$M = 100\,\frac{x - \mu}{\sigma} \tag{32}$$

Since M is the rainfall anomaly normalized by σ, then within reasonable limits it permits a comparison of the rainfall anomaly for different locations and months. Even though it is much simpler to estimate M of the BMI than Z of the PDSI, Equations (22a)–(30) derived for computing the Z index of the PDSI can be similarly applied to obtain M versus period for the BMI. Similarly, the worst cumulative M versus duration is also assumed to change linearly as the extreme drought line representing the worst Z versus duration for the PDSI (Figure 2). For the reasons given in Section 5, we did not attempt to improve the BMI.

4. SPI

McKee *et al.* (1993) defined the SPI as the number of standard deviations that the observed cumulative rainfall at a given time scale would deviate from the long-term mean. As a single numeric value, the SPI can be compared across regions with markedly different climates. The Colorado Climate Center, the Western Regional Climate Center and the National Drought Mitigation Center use the SPI to monitor drought in the USA (Edwards and McKee, 1997). Since the cumulative precipitation may not be normally distributed, McKee *et al.* (1993) transformed the data approximately to the normal domain to standardize the drought index. The time scale of the SPI is also flexible, which is an attractive feature because it is possible to experience wet conditions at one time scale but dry conditions at another simultaneously. For example, soil moisture, which typically responds to precipitation relatively quickly, may soon be depleted in a brief drought spell, whereas streamflow and groundwater, which are affected by longer term precipitation anomalies, may still be relatively normal.

Even though, theoretically, the time scale of SPI is flexible, in practice a monthly precipitation time series is ‘smoothed’ with a moving window of width equal to the number of months desired, e.g. a 3 month SPI would use a moving window of a 3 month width. Edwards and McKee (1997) selected a 3 month SPI for a short-term drought index, a 12 month SPI for an intermediate-term drought index, and a 48 month SPI for a long-term drought index. The window is *non-centred* such that the filtered series depends only on the present and past values of the time series, e.g. for a 3 month window, the new smoothed series $x'_t, t = 1, 2, \ldots, n$ are given by

$$x'_t = \frac{1}{3}\sum_{i=0}^{i=2} x_{t-i} \tag{33}$$

The filtered data are broken into 12 monthly time series, which McKee *et al.* (1993) individually fitted with a gamma distribution $g(x)$, that can describe skewed hydrologic variables without the need for log-transformation (Chow *et al.*, 1988). It is possible to use other distributions, as long as they fit the data adequately. The probability density function of the gamma distribution is

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for } x > 0 \tag{34}$$

where $\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy$ (the gamma function), and α and β are the shape and scale parameters respectively, whose maximum likelihood estimators are (Edwards and McKee, 1997)

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \tag{35}$$

$$\hat{\beta} = \frac{\overline{x}}{\hat{\alpha}} \tag{36}$$

where $A = \ln(\overline{x}) - \sum \ln(x)/n$ and n is the number of observations. After finding α and β, the cumulative probability $G(x)$ corresponding to an observed precipitation is

$$G(x) = \int_0^x g(x) dx \equiv \frac{1}{\hat{\beta}\Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}-1} e^{-x/\hat{\beta}} dx \tag{37}$$

The incomplete gamma function of Equation (37) is undefined for $x = 0$, yet it is possible to get months with no precipitation. Therefore, Edwards and McKee (1997) suggested that the actual probability of non-exceedance $P(x)$ should be given by

$$P(x) = q + (1 - q)G(x) \tag{38}$$

where q is the probability of $x = 0$. If m is the number of zeros in a sample of size n, then q can be estimated by m/n. The inverse normal (Gaussian) function is applied to $P(x)$ to obtain the SPI. From our experience, the smoothing of precipitation data often eliminates or greatly decreases the number of months with zero precipitation; e.g. for a 6 month SPI, having a zero in the smoothed time series is only possible if there are six consecutive months that are completely dry, which is rare for our study area. Since the problem of zero values seldom arises in our study, q in Equation (38) is set to zero.

Transforming $P(x)$ to the SPI is an equi-probability transformation, whereby a variate from one distribution (i.e. gamma) is transformed to another variate of a prescribed distribution (Gaussian normal) such that both the new and old variates have the same $P(x)$ (Figure 3). In Figure 3, a 3 month precipitation amount (March–May, MAM) is converted to 3 month SPI that has a zero mean and unit variance, where a MAM precipitation of 300 mm corresponds to an SPI value of 0.39, but both variates have the same $P(x)$ of 0.65. According to McKee *et al.*'s (1993) definition of drought categories, SPI ≥ 2.0 means an extremely wet spell, $1.99 \geq$ SPI ≥ 1.0 means very to moderately wet, $0.99 \geq$ SPI ≥ -0.99 means near normal, $-1.0 \geq$ SPI ≥ -1.99 means moderately to severely dry, and SPI < -2.0 means a extremely dry spell. A drought event is considered to have occurred any time the SPI is continuously -1.0 or less. The event ends when the SPI becomes positive. Therefore, each drought event has a well-defined duration.

It is evident that the frequency, duration, and intensity of drought at a given location and its SPI value are dependent on the time scale, as shown by three different SPI curves of Singida in Central Tanzania (Figure 4), where the 48 month SPI curve is relatively smooth compared with the 12 month SPI curve, and the 6 month SPI is relatively rugged. For example, for Singida in July and August 1969, the 6 month SPI values were -2.7 and -3.0 respectively, indicating a severe drought, whereas the 12 month SPI values were both 0.7, indicating near-normal conditions, and the 48 month SPI values were both 1.95, indicating a very wet period.

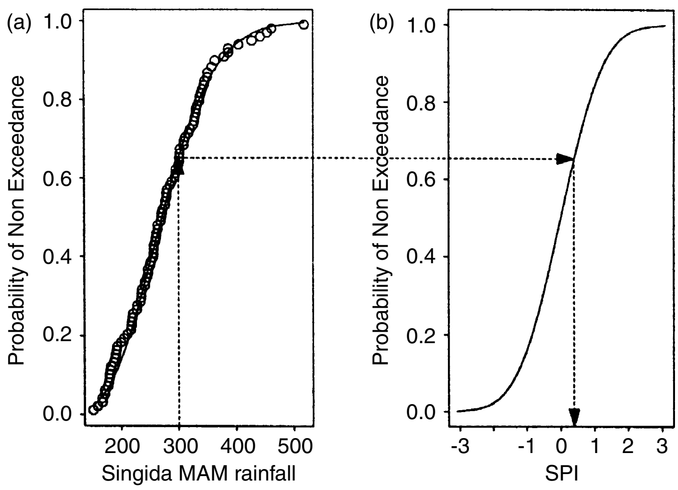

Figure 3. (a) The non-exceedance probability $P(x)$ plot of the MAM precipitation data of Singida (1900–96), where data points denote the cumulative probability plot of the actual 3 month precipitation totals and the continuous curve denotes the fitted gamma distribution. (b) The corresponding 3 month SPI distributed according to a Gaussian normal

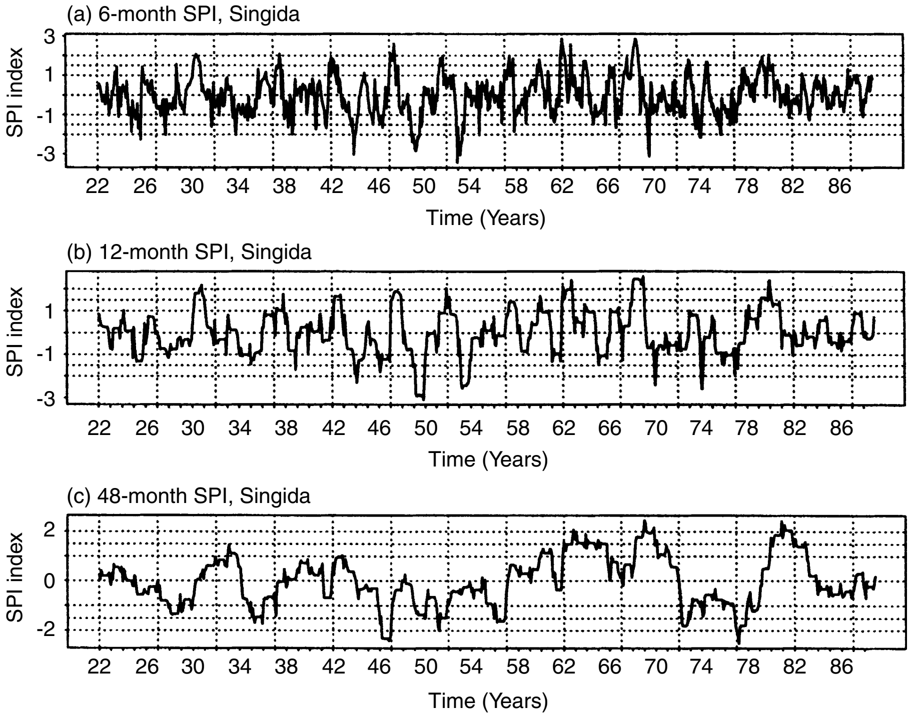

Figure 4. Time series of the 6, 12 and 48 month SPI of Singida, central Tanzania

4.1. Suggested improvements to the SPI

The SPI algorithm has several properties that merit revision. First, there is still disagreement regarding the type of probability distribution needed to estimate the non-exceedance probability $P(x)$ of the smoothed precipitation time series, even though gamma has been the most commonly used distribution. The SPI value computed depends on the distribution fitted to the precipitation data. We propose using a plotting-position formula to estimate $P(x)$, which is preferable if the data set is reasonably long, say about 90 years or more, so that we can estimate $P(x)$ ranging from 0.01 to 0.99. Several popular plotting-position formulae in hydrology — which attempt to achieve an almost quantile-unbiased fit for different distributions (Maidment, 1993) — are of the general form

$$q_i = \frac{i - a}{n + 1 - 2a} \tag{39}$$

where i is the rank order, n is the sample size, and a is a parameter. Cunnane (1978) discussed the characteristics of these formulae and recommended $a = 0.40$ as being suitable for estimating unbiased quantiles for a wide range of distributions. The most popular plotting-position formula is the Weibull plotting formula ($a = 0$ in Equation (39)), which has been shown to be suitable for estimating unbiased $P(x)$ for almost all distributions (Maidment, 1993). Since plotting-position formulae only use data ranks, they are non-parametric; so, by using them to estimate the $P(x)$ of the smoothed precipitation series, we use the SPI algorithm in a non-parametric framework, which has attractive properties — the most obvious being their ability to handle disproportionate outliers. Each of the 12 sub-series corresponds to a combination of months, e.g. a 6 month SPI could be based on January to June, or February to July data, and so there should be 12 such sub-series regardless of the length of the smoothing window.

Comparing the SPIs obtained by the parametric and non-parametric methods for the Singida station (Figure 5), noticeable differences are only found for very extreme events, especially for the 12 month SPI. This is partly because the Weibull formula cannot estimate $P(x)$ less than $1/(n+1)$ or greater than $n/(n+1)$,

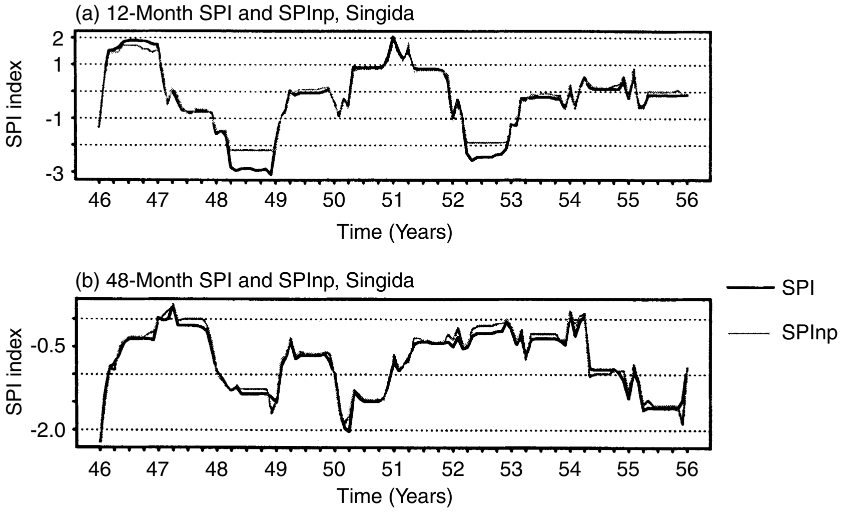

Figure 5. Time series of the (a) 12 month and (b) 48 month SPI and non-parametric SPI (SPInp) of Singida. The grey dotted line is the non-parametric SPI

whereas one can estimate such extreme probabilities using a fitted distribution even though the possible error associated with it could be significant, especially if the distribution is fitted with limited data. Once the SPI has exceeded the extreme threshold of -2.0, however, it is less relevant to know how much further it goes down. Therefore, the non-parametric approach avoids the uncertainties of the parametric approach, and without compromising the amount of information it could provide under extreme droughts.

Second, we briefly tested the effect of the base period used in calibrating the distribution functions on the SPI values. Edwards and McKee (1997) used a fixed base of 30 years to fit the necessary gamma parameters. We found minimal variations in the SPI computed as we increased the length of the calibrating period from 62 to 97 years. Apparently, for East African data, as long as the calibration period is reasonably long, then increasing the calibration period does not lead to significant changes in the level of drought severity.

Third, the original SPI represents Z scores (number of standard deviations away from the mean) of a normal distribution determined from mapping the probability distribution of the smoothed precipitation totals to the normal domain. This normality assumption is generally not a good approximation for an SPI of 6 months or shorter time scales, because such rainfall series are mostly positively skewed and transforming them to the normal domain will inevitably cause undesirable distortion, especially in the right-hand tail of the distributions. Therefore, we replaced the normal distribution in the SPI with the Pearson type III distribution (P3) to take care of the skewness of precipitation. Furthermore, we applied the regional 'flood-index' method (Maidment, 1993; Hosking and Wallis, 1997) to obtain the regional P3 curves so that a drought comparison across a region is possible. The term 'index flood' arose because early applications of the procedure were to flood data, but the method is also applicable to drought analysis. A brief description of the procedure is provided below.

Suppose there are data at N sites, where the ith site has a sample size n_i, and observed data P_{ij}, $j = 1, \ldots, n_i$. Let $P_i(F)$, $0 < F < 1$, be the quantile function of the frequency distribution at site i. We may then rewrite

$$P_i(F) = \mu_i q(F) \quad i = 1, \ldots, \mathrm{N} \tag{40}$$

where μ_i is the index flood or the mean of at-site i, and $q(F)$ is the regional growth curve, a dimensionless quantile function common to every site, or the regional frequency distribution of the dimensionless, rescaled data, P_{ij}/μ_i, $j = 1, \ldots, n_i$, $i = 1, \ldots, N$. The index-flood procedure is premised on a number of assumptions: observations at any given site are identically distributed and serially independent, observations at different sites are independent, and the frequency distributions at different sites should be identical apart from a scale factor. These assumptions are only approximately attained by most rainfall data.

In order that the modified SPI is comparable across East Africa, we applied the regional analysis to the whole of East Africa as one homogeneous region. From the homogeneity test of Hosking and Wallis (1997), which assessed whether the at-site (grid) variation of the sample L-moments was consistent with what would be expected of a homogeneous region, we found this assumption to be acceptable for East Africa. After smoothing the monthly data series with a window representing the scale of interest, the individual grid data were divided by the respective grid means to obtain the dimensionless grid-based variables.

Among five distributions (generalized logistic, generalized extreme value, generalized Pareto, P3 and Wakeby) fitted to the rescaled data by the L-moment estimators, we found the P3 to be acceptable for 30 out of the 31 grid points. There is considerable acceptance of the P3 or the logarithmic-P3 (LP3) distributions in water resources investigations (Vogel and McMartin, 1991), partly because P3 can assume a wide range of distribution shapes, including the gamma and normal distributions as special cases of P3:

$$f(x) = \frac{|\chi|}{\Lambda(x)}[\chi(x-m)]^{\lambda-1}e^{-\chi(x-m)} \tag{41}$$

where χ, λ and m are the scale, shape and location parameters respectively. When $\chi > 0$, the random variable x is positively skewed with m as the lower bound, i.e. $m \leq x \leq +\infty$. Similarly, m is the upper bound of a negatively skewed P3 distribution, but most precipitation time series are positively skewed. When $\chi > 0$ and $m = 0$, P3 reduces to a gamma distribution. As $\lambda \to \infty$, the skewness coefficient γ goes to zero, since $\gamma = 2\chi/|\chi|\lambda^{1/2}$, and P3 converges to a normal distribution. For $\lambda = 1$, and $\gamma = 2$, P3 becomes the two-parameter exponential distribution. The parameters and regional curves of the P3 regional distributions are shown in Table III and Figure 6 respectively.

Table III. The regional P3 distribution parameters obtained from the precipitation totals of time scale of analysis ranging from 2 to 36 months

Scale of analysis (months)	Standard deviation σ	Skewness Γ	Shape parameter λ
2	0.56	1.22	2.686
3	0.46	1.02	3.820
6	0.30	0.71	8.007
9	0.24	0.57	12.495
12	0.20	0.51	15.561
16	0.18	0.49	16.817
24	0.15	0.47	17.773
36	0.12	0.44	20.624

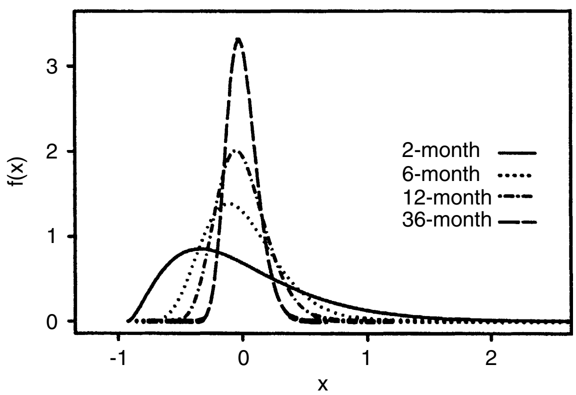

Figure 6. Four regional P3 probability density functions of various degrees of skewness used to develop the modified 2 to 36 month SPI

As expected, the standard deviations of the regional curves decrease as the scale of analysis is increased. For a long duration, say 36 months, the mean value of 36 consecutive months of rainfall totals is relatively big. When this big number divides the smoothed series the resulting series are bound to be small, and the spread about the mean is also small. Table III shows the gradual increase of λ as the time scale increases. Since a normal distribution has $\lambda = \infty$, it seems that monthly rainfall series smoothed by a large enough window (>24) approximate well to a normal distribution. This is in consonance with the central limit theorem, which states that the sample mean of identically distributed variables is approximately normal (Larsen and Marx, 1981). What a large smoothing window does is to create a new series composed of consecutive sample means of sample size equal to the window size. The larger the window size, the closer the sample becomes normally distributed, e.g. 60 month SPI.

From Figure 6, we see that the regional probability distributions of short time scales, of say 6 months or less, are clearly positively skewed. For the P3, a quantile-unbiased plotting-position to estimate the quantiles depends on β, and hence the sample skewness γ is needed. Since Equation (39) cannot be used for P3, Nguyen *et al.* (1989) developed an approximate plotting position for the P3

$$q_i = \frac{i - 0.42}{n + 0.3\gamma + 0.05} \tag{42}$$

This formula is suitable for $-3 \leq \gamma \leq 3$ and samples size in the range of $5 \leq n \leq 100$, which are ranges appropriate for our study. The P3 plotting positions obtained from Equation (42) were transformed into the standardized P3 variates. The γ needed in Equation (42) is estimated by the method of moments:

$$\hat{\gamma} = \frac{1}{s^3}\left(\frac{\sum_{i=1}^{n} x_i^3}{n} - 3\overline{x}s^2 - \overline{x}^3\right) \tag{43}$$

where $\overline{x}$ is the sample mean and s is the standard deviation. Several investigators (e.g. Bobee and Robitaille, 1975) have shown that Equation (43) would underestimate γ, especially for small samples, since, theoretically, $\max|\gamma| = n^{1/2}$. Bobee and Robitaille (1975) derived an empirical formula to adjust the skewness for P3:

$$\gamma_{\mathrm{u}} = \overline{\gamma}\left[\left(1 + \frac{6.51}{n} + \frac{20.2}{n^2}\right) + \left(\frac{1.48}{n} + \frac{6.77}{n^2}\right)\overline{\gamma}^2\right] \tag{44}$$

where $\overline{\gamma}$ is the sample mean of γ, each of which computed from a P3 sample of size n (usually replaced by $\hat{\gamma}$, since only one sample is typically available). Figure 7 compares the original SPI with the modified 6 month SPI for Tabora and Singida in central Tanzania. As expected, the differences between them mainly show up in the extreme values, since the discrepancies resulted from approximating a P3 with a normal distribution increase towards the tails. Typically, the P3-based SPI will have smaller negative extremes than the Gaussian normal SPI, especially for a short time-scale SPI (Figure 7), e.g. the Gaussian normal 6 month SPI for Tabora was −2.87 in May 1949, whereas the P3 6 month SPI was −1.86, which should be more realistic because the 6 month precipitation totals are positively skewed.

McKee *et al.* (1993) arbitrarily chose SPI threshold values ranging from +2 to −2 in steps of 0.5 to assign the drought categories. For example, they associated an SPI value between −1 and +1 with normal or near-normal conditions, which for a Gaussian normal means a $P(x)$ ranging from 0.16 to 0.84. Such a drought classification scheme cannot work with the P3-based SPI. This is because standardized P3 variates corresponding to a given probability vary in magnitude according to the regional shape factor γ. In the modified SPI, each time scale of analysis should have its own classification thresholds depending on γ. Thus we propose a new drought classification table, as shown in Table IV. This assumes that extreme wet and dry events are those with $P(x)$ values of 0.98 and 0.02 respectively.

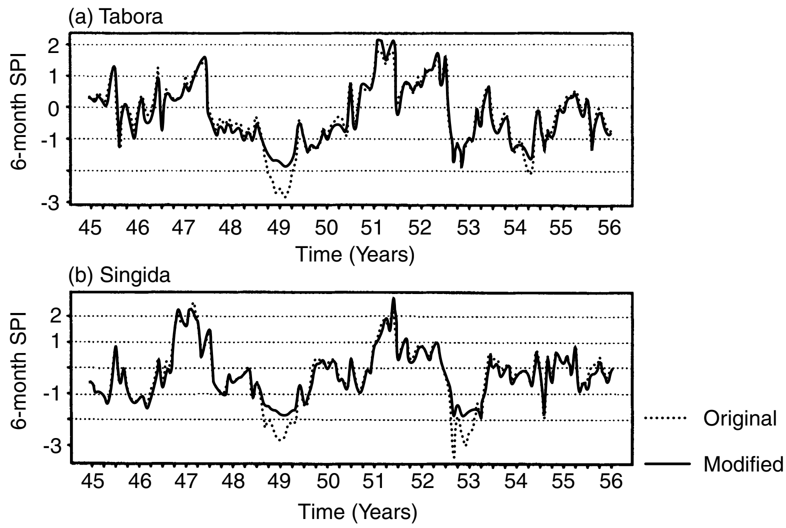

Figure 7. A comparison between the modified and original 6 month SPI for (a) Tabora and (b) Singida, both located in Tanzania, East Africa

Table IV. Drought threshold classifications expressed in terms of non-exceedance probability $P(x)$ for both the P3-based and Gaussian normal-based, n month SPI

Drought classification	Non-exceedance probability $P(x)$	P3-based SPI				Normal-based SPI
		2 months	6 months	12 months	36 months	
Extremely wet	>0.98	>2.63	2.41	2.31	2.28	2.05
Very wet	0.95–0.9799	1.91–2.63	1.82–2.41	1.78–2.31	1.76–2.28	1.64–2.05
Moderately wet	0.80–0.9499	0.73–1.91	0.79–1.82	0.81–1.78	0.81–1.76	0.84–1.64
Near normal	0.20–0.7999	−0.84–0.73	−0.86–0.79	−0.86–0.81	−0.86–0.81	−0.84–0.84
Moderately dry	0.05–0.1999	−1.24 to −0.84	−1.42 to −0.86	−1.49 to −0.86	−1.51 to −0.86	−1.64 to −0.84
Very dry	0.02–0.0499	−1.37 to −1.24	−1.66 to −1.42	−1.77 to −1.49	−1.81 to −1.51	−2.05 to −1.64
Extremely dry	<0.02	<−1.37	<−1.66	<−1.77	<−1.81	<−2.05

Under the modified SPI, there is a noticeable difference in the threshold of the extreme moisture conditions. The number of standard deviations from the mean needed to signal an extreme drought condition (with a $P(x) = 0.02$) varies progressively from −1.37 for the 2 month SPI to −1.81 for the 36 month SPI. For these SPI indices, the corresponding numbers of standard deviations from the mean to reach extremely wet conditions decrease from 2.63 to 2.28. However, the subtle difference between the original and the P3-based SPI could lead to different categories of drought being identified in the analysis.

5. ASSESSMENT CRITERIA TO IDENTIFY A DROUGHT INDEX APPROPRIATE FOR A REGION

Although there is no drought index that is inherently superior to others in all circumstances, some indices are better suited than others for certain regional applications. Ideally, we wish to know the most suitable index for East Africa; but realistically, no one index can perfectly track the four principal dimensional (three spatial, one temporal) variations of the climate system. Yevjevich *et al.* (1978) and Redmond (1991) discussed criteria that can be used to gauge the suitability of a drought index. Using the PDSI, BMI, SPI and East Africa as a case example, and with reference to Yevjevich *et al.*'s (1978) suggested criteria, we identified and applied eight assessment criteria to determine a drought index most appropriate for monitoring droughts on a regional basis: (1) characteristics, statistical properties and variability of drought indices; (2) detailed analysis of a major historical drought; (3) adaptation of drought indices to local climate; (4) unbounded index values; (5) spatially 'invariable' property; (6) flexible time scale; (7) data requirement and availability; and (8) interpretability.

5.1. Characteristics, statistical properties and variability of drought indices

Comparing the original and modified PDSIs for three locations (Figure 8), it was observed that the former produced unrealistic or erroneous scenarios for the drier northern East African locations such as Lodwar, indicating continuous drought from 1960 to 1985. A detailed analysis of the original PDSI algorithm showed that R and RO were typically zero in dry areas such as Lodwar. Unlike the wetter areas, the PL in semi-arid areas was usually zero or very small, which did not decrease the CAFEC precipitation $\hat{P}_{w,j}$ much (see Equation (12)). Consequently, the CAFEC precipitation was always much bigger than the actual amount of precipitation available, which seemed to be the primary cause of the unrealistic, perpetual drought episode in dry areas such as Lodwar. Given that the modified PDSI provided a more realistic drought scenario for these stations, it seems that the revisions suggested for computing the CAFEC precipitation (see Equations (19) and (20)) have resolved this problem.

It is also noted that the departure coefficient K_j obtained by Equation (15) always returned values that were less than 0.6 for dry places, such as Lodwar, and values in the 1.0 to 2.0 range for moderately wet areas. The differences between the original and modified PDSIs for the wetter regions are less pronounced, partly because shifting between *X1, X2,* and *X3* reinitializes the system, so that differences between these two PDSIs do not propagate along the entire time series. The extreme drought values resulting from the modified PDSI seem

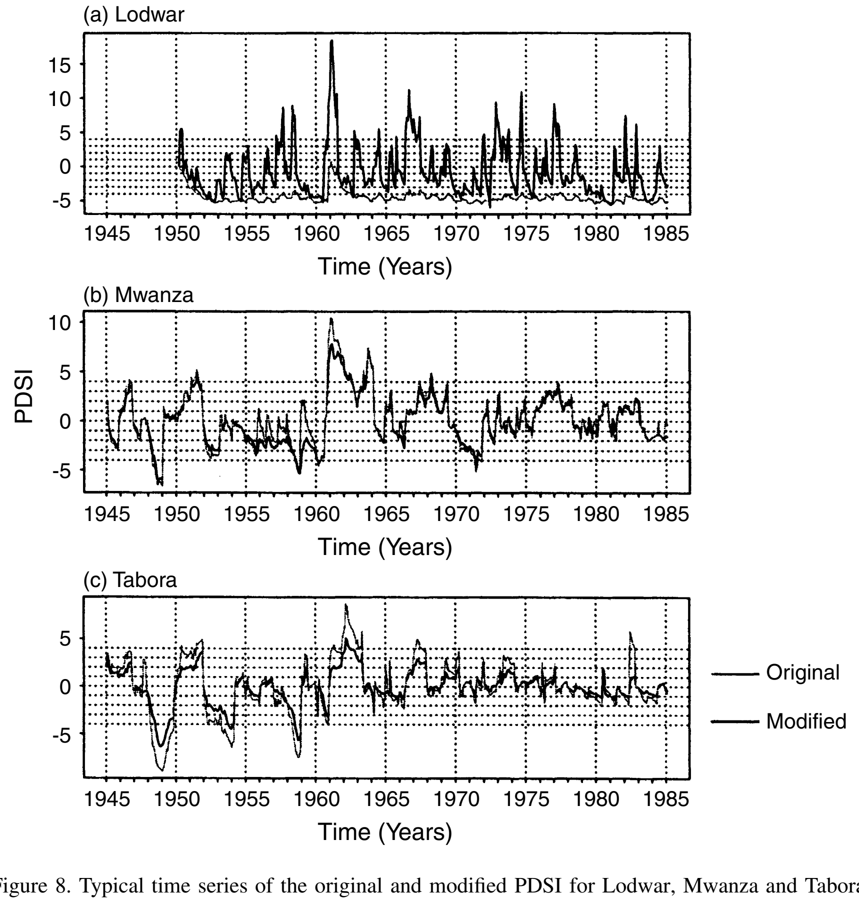

Figure 8. Typical time series of the original and modified PDSI for Lodwar, Mwanza and Tabora

to be less than those obtained from the original PDSI (Figure 8(c)), probably because of the revised at-site drought recursive formula (Equations (29)–(31)). However, the extreme positive values for both PDSIs were observed to be way beyond +4, the threshold for extremely wet events. The original PDSI was developed with respect to extremely dry events having a threshold of −4, and assuming a symmetrical distribution, extremely wet events would have a threshold of +4. However, this assumed symmetric distribution is likely untrue, given precipitation data are mostly skewed.

The modified PDSI does not seem to be very sensitive to the actual evaporation values, given that testing the algorithm with Thornthwaite monthly evaporation and average monthly pan measurements produced little difference in the PDSI values. In other words, most of the variability comes from the rainfall data; the evaporation data contribute little to the total variability, partly because, compared with the former, variations in the latter are relatively small.

Even though the main PDSI recursive formula appears as an AR(1) model (see Equation (31)), it is not purely AR(1) because at times the index shifts abruptly between *X1, X2* and *X3*. Nevertheless, due to Equation (31), the PDSI for a month is linearly related to that of the previous month, and PDSI generally exhibits some AR(1) characteristics, such as an exponential autocorrelation function. A spectral analysis reveals the existence of a 5 to 9 year long-term memory in both the original and modified PDSIs (figure not shown), as was also found by Guttman (1998) in the US PDSI data. The long-term memory could partly result from the way the water balance is computed in the index. Since it is usually difficult to justify a long-term memory of 5 years or more in droughts, we should be cautious in interpreting the results obtained from both the modified and the original PDSIs.

Figure 9 shows that there is a high correlation (greater than 0.8 in many places) between the modified PDSI and the BMI, which again suggests that most of the variability in the PDSI is due to precipitation alone. Some parts of East Africa, namely southwestern Tanzania and part of the western Kenya highlands, show a lower correlation between the two indices, probably for two reasons. Locations that are further away from the equator tend to experience higher seasonal variations in temperature and so are the variations in ET. It seems that the BMI and the PDSI differ from each other in locations that are further than $\pm 6^{\circ}$ in latitude away from the equator partly because the BMI does not consider ET. However, the lack of correlation may be attributed more to the aforementioned areas being highlands; this is because the evaporation computed by the Thornthwaite method, which does not consider the influence of altitude, is likely to be inaccurate, a shortcoming of the PDSI if the Thornthwaite method is used.

Although the BMI avoids some of the shortcomings of the PDSI, it still shares with it one disadvantage, in that it simplifies drought occurrences as purely AR(1), and more so than the PDSI because the PDSI may shift abruptly at times among the three pseudo indices. Depending on the coefficient in the AR(1) process, a sudden shock in the series may take a very long time to die down (Figure 10(a)). The PDSI does not have as much memory and so should be more realistic than the BMI, given that a drought lasting many months or even years may end abruptly with 1 or 2 months of intense rainfall. The lack of any significant partial autocorrelation in both the BMI and the PDSI is a further demonstration of AR(1) properties. Conversely, the 12 month SPI exhibits some finite moving average properties, where the autocorrelation decreases to zero by a certain period but the partial autocorrelation persists for a long while (Figure 10(f)).

5.2. Detailed analysis of a major historical drought

Both PDSI indices are also checked with the well-known historic drought event in 1949. This was the worst recorded drought year in East Africa in the 20th century, when most places in East Africa received annual rainfall in the 20th percentile or less. In 1949, the modified PDSI was less than −3.0 for most of Tanzania and eastern Kenya, indicating that 1949 was a severe drought year. A comparison with the original PDSI (Figure 11(a)) shows that the modified PDSI (Figure 11(b)) was generally better at capturing the 1949 drought. Although both PDSI indices show the same trends at some stations, at other stations there are important differences. For example, the modified PDSI shows that Dar es Salaam experienced severe dry conditions just like the rest during May–October 1949, whereas the original PDSI showed that Dar es Salaam had near-normal moisture conditions during the May–July 1949 period; this was not true, since in 1949 Dar es Salaam (average rainfall 1100 mm) received the lowest annual rainfall (438 mm) in the 1900–97 record.

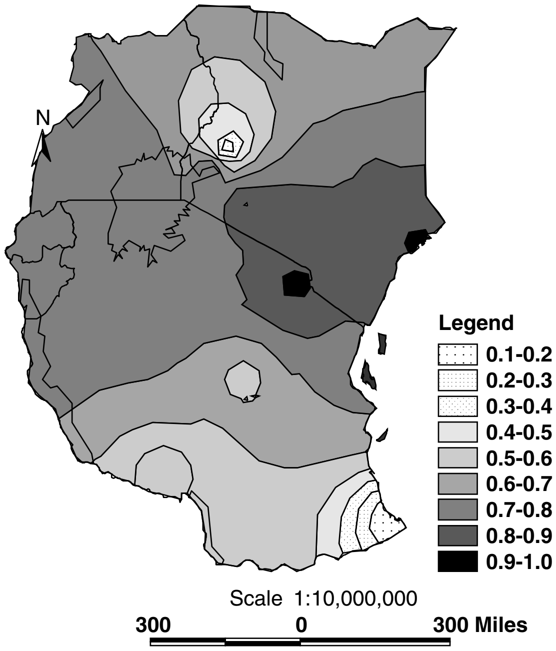

Figure 9. The spatial correlation between the PDSI and the BMI for East Africa

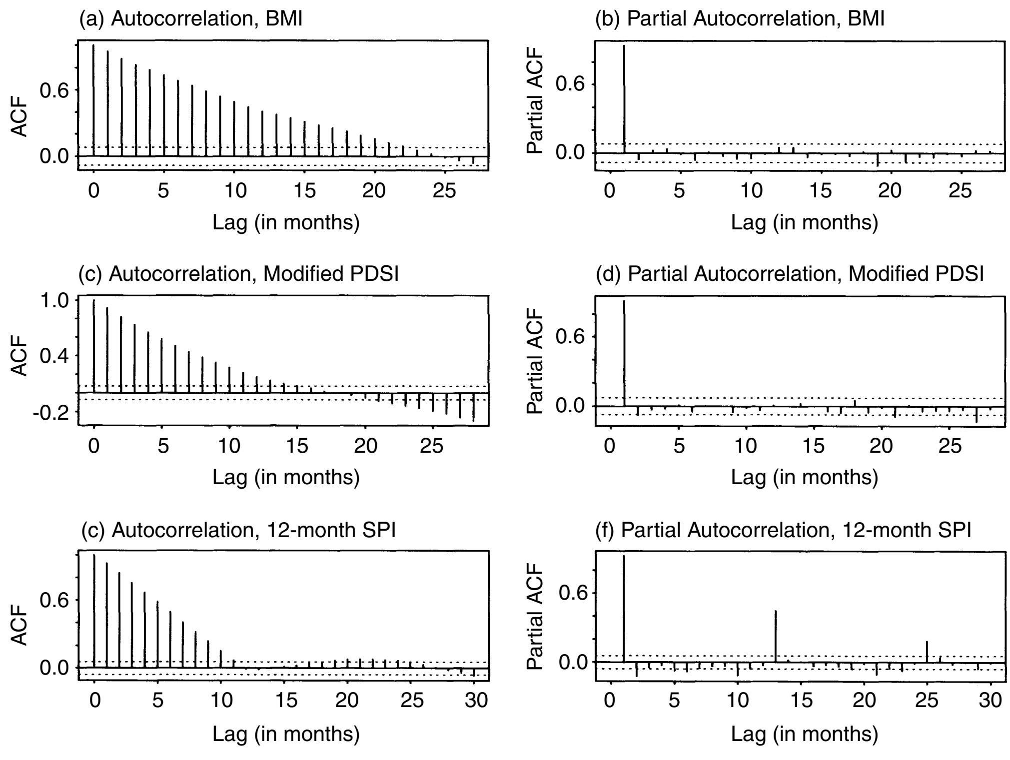

Figure 10. Autocorrelation and partial autocorrelation of the BMI (a and b) and that of the modified PDSI (c and d) for Kampala, Uganda. The dotted horizontal lines represent the intervals within which the correlations are significant at the 95% confidence level

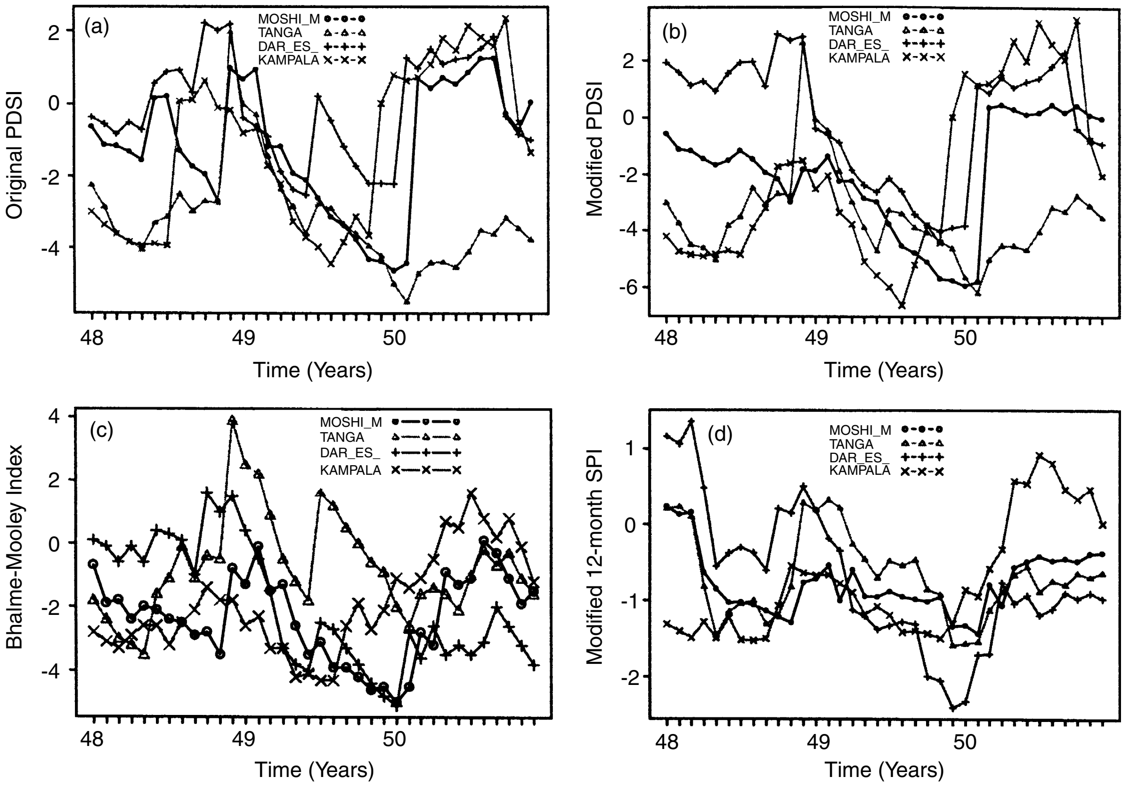

Figure 11. A comparison between (a) original, (b) modified PDSI, (c) BMI, and (d) modified 12 month SPI of selected climate stations of East Africa during the drought period of January 1948 to December 1950

The 12 month SPI also shows that Dar es Salaam suffered from severe drought during May–October 1949 but indicated that the drought lasted until the middle of 1950, whereas the modified PDSI indicated that it went away in the early 1950s, which was not quite true (Ntale, 2001). Figure 11 shows that the 1949 drought patterns indicated by the BMI tend to have more scatter than those of the PDSI and SPI. Furthermore, the BMI shows that Tanga's drought condition ended abruptly in the middle of 1949, which is incorrect. The 12 month SPI and the modified PDSI provide a more representative 1949 drought scenario for East Africa than the BMI.

5.3. Adaptation to the local climate

Yevjevich *et al.* (1978) suggested that, for a drought index to be effective, it should be derived locally, be adapted to the climate of the territory, and conceptually and comprehensively describe droughts in the region. The modified SPI, which involves deriving a P3 distribution regionally, satisfies this qualitative criterion. Although the modified PDSI and BMI are also calibrated locally, they still retain some empirical relationships derived from a different region, e.g. although Palmer (1965) assumed that Z changes more or less linearly with duration because of his observations for the study sites in USA, there is little basis to believe that it will always be a linear relationship elsewhere.

5.4. Unbounded index values

A good drought index should be able to attain unprecedented values if extraordinary climate behaviour occurs in the future, or an index's temporal normalization with respect to the background climatology should be a continuous process. Among the three indices, the SPI best approaches this 'open-ended' behaviour because its values are not bounded. By virtue of their algorithms, the PDSI and BMI are theoretically bounded by a lower value of −4, even though in practice they both could go beyond these bounds because of inconsistencies in their algorithms. The original PDSI parameters were obtained with respect to the extreme droughts of the American Great Plains of the 1930s. However, fixing the extreme values of the PDSI reduces its ability to monitor the occurrence of exceptional droughts.

5.5. *Spatial invariability*

It is desirable for a drought index to be spatially 'invariable', such that it presents more or less the same information regardless of the site being investigated, a prerequisite for any inter-site comparison of drought conditions to be meaningful. To investigate this consistency, we compared the uniformity of the power spectral patterns of the PDSI and SPI for East Africa (Guttman, 1998), which reveals some important differences. The power spectra of the SPI show more consistent characteristics than that of the PDSI (Figure 12), which agrees with the results of Guttman (1998), who compared the PDSI and SPI for the USA. The PDSI's relatively tedious procedure involving multiple variables could be counterproductive, as reflected in the diverse nature of its power spectral plots (Figure 12(b)). In contrast, the simpler nature of the SPI, involving only precipitation, produces more consistent results, giving us more of a basis to compare results between different parts of East Africa.

5.6. *Flexible time scale*

Unlike the PDSI or BMI, the SPI can be computed almost at any time scale desired. Since soil moisture, streamflow, and reservoir storage respond to precipitation shortage at different time scales, this flexibility allows us to track a wide range of drought types, e.g. a 12 month SPI for tracking intermediate droughts and a 24 or 36 month SPI for long-term droughts. On comparing the modified PDSI and the 2 to 36 month SPIs (both original and modified), it seems that the former is only strongly correlated to the 12 month SPI for most stations and 11 month SPI for a few stations (Figure 13). This shows that the PDSI is probably not suitable for tracking droughts at times scales shorter than a calendar year.

Albeit that most drought indices are computed at a monthly or longer time scale, Byun and Wilhite (1999) suggested that a daily time step should be used, because sometimes a region suffering from drought could return to normal with only a day's rainfall. For example, if there were heavy rains only on 1 December and 31 January, then a continuous 60 days of no precipitation between 2 December and 30 January may not be detected by a monthly index in spite of there being a serious water shortage arising from 60 continuous days of no rainfall. The SPI allows the use of daily time step with minimal alterations. Although we know of no attempt to compute the SPI using a daily time step, a daily SPI should track the drought conditions more precisely than that based on monthly data.

5.7. *Data requirements and availability*

The PDSI requires long time series of precipitation and ET, as well as spatially distributed soil moisture properties; these are hard to obtain in East Africa, especially in the more remote areas. In contrast, the SPI and BMI only require precipitation data, and yet they both (Figures 10 and 13) correlate well with the PDSI. In this regard, since East African precipitation data are reasonably available, it is advisable to adopt the SPI or BMI rather than the PDSI.

5.8. *Interpretability*

A good drought index should be easy to interpret if it is to become an effective tool in monitoring droughts. Among these indices, the SPI is likely the easiest to interpret because its index value represents the number of P3 standard deviations from the mean of a location at a particular period, e.g. if the 12 month SPI of a location in November is unity, then this means that the total rainfall amount for the preceding 12 months until November is equal to the mean plus one standard deviation. No such a straightforward

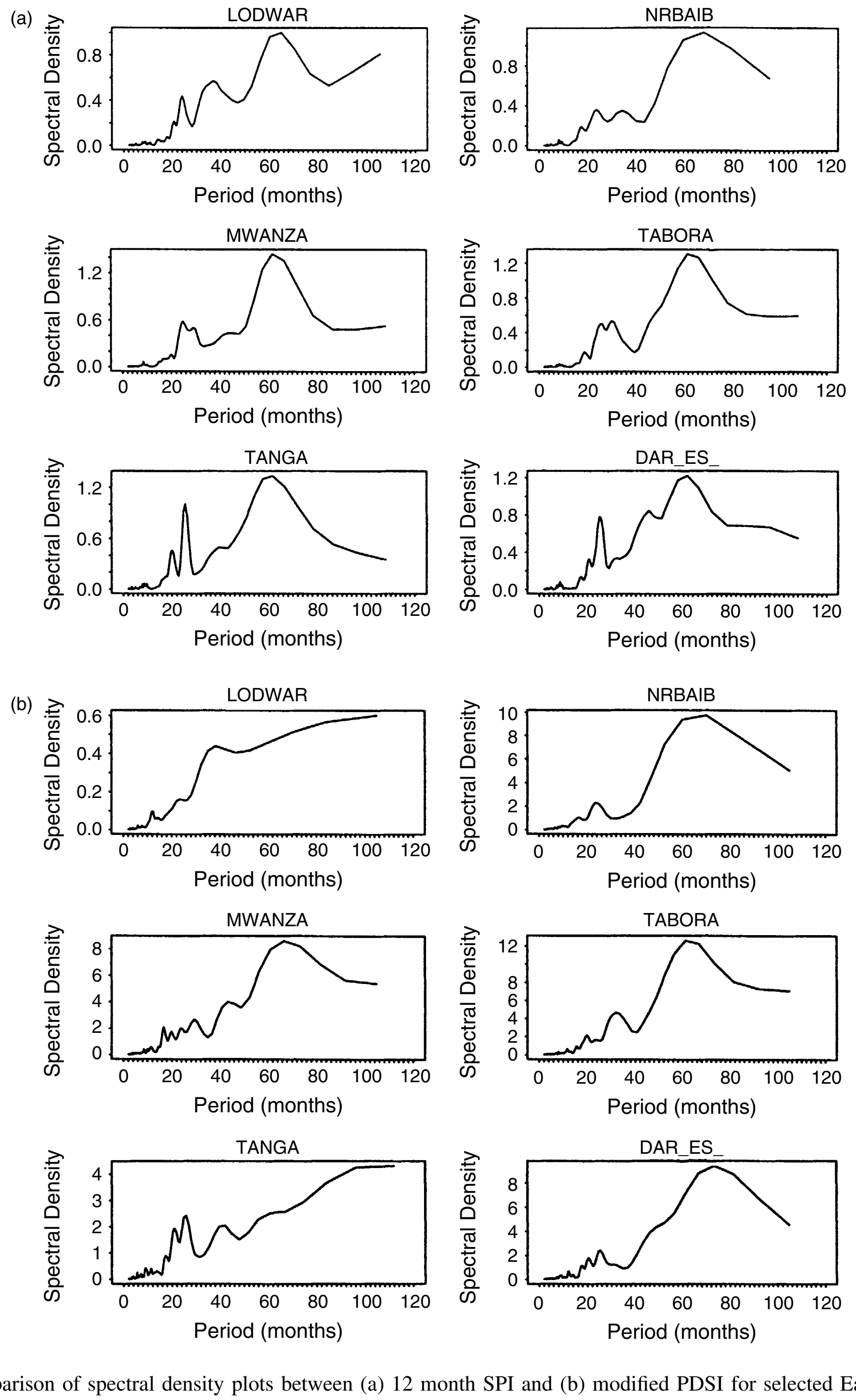

Figure 12. A comparison of spectral density plots between (a) 12 month SPI and (b) modified PDSI for selected East African stations

interpretation can be derived for the PDSI or BMI. As the intended audience gets wider, and probably less knowledgeable about the index details, it is desirable to understand what the index values indicate without having to know the details and caveats of the index's algorithm. In conclusion, the multi-criteria assessment seems to indicate that, among the three indices, the SPI is likely the best choice for detecting droughts in East Africa.

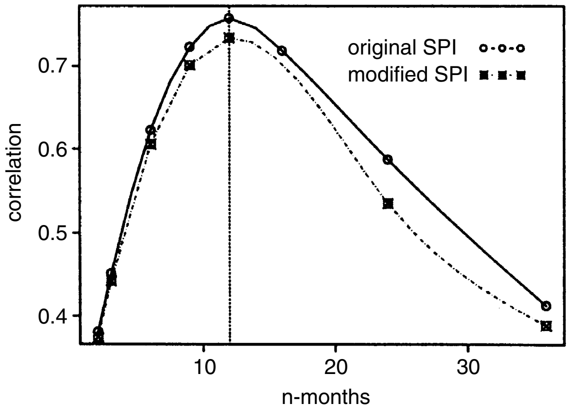

Figure 13. A correlation between PDSI and the n month SPI for Tabora station, where n ranges from 2 to 36 months. The dashed curve refers to the modified P3-based SPI and the dashed vertical line marks the 12 month time scale ($n = 12$)

In a similar manner, the above assessment criteria can also be applied to other drought indices and regions to determine the most appropriate drought index on a regional basis.

6. SUMMARY AND CONCLUSIONS

We have analysed and modified (when necessary) three drought indices: the PDSI, the BMI and the SPI, applicable to regions of varying climates. Given that the original PDSI designed for the USA did not give reasonable results for some parts of East Africa (especially the drier parts), we modified the PDSI's recursive formula, potential runoff, and Z index, which produced more realistic results than the original PDSI for East Africa's 1949 drought.

We improved the SPI in two ways. First, instead of fitting a gamma distribution to the 'smoothed' precipitation data, we used an unbiased P3 plotting-position formula (Nguyen *et al.*, 1989) to reduce the possible effects of outliers. Second, we derived the final index value by transforming the non-exceedance probabilities into standard P3 variates using the regional flood-index method instead of a Gaussian normal distribution, which would introduce distortion in the distribution tails for skewed precipitation data. The modified SPI produced results that are more representative of East Africa's drought conditions than the original SPI of McKee *et al.* (1993).

Using these three drought indices and East Africa as a case example, we then identified eight assessment criteria to determine the most appropriate index for detecting the initiation, evolution, termination and severity of drought events on a regional basis. Although the BMI only uses precipitation data, its index values still correlate strongly to the modified PDSI in East Africa, which suggests that precipitation data alone could explain most of the variability of East African drought. However, with respect to the 1949 drought, drought patterns indicated by the BMI tend to have more scatter than those of the PDSI and SPI. Our analysis showed that the SPI is more suitable for monitoring droughts in East Africa than the PDSI and BMI, because it is easily adapted to the local climate, it has modest data requirements, it produces more consistent spectral patterns across East Africa than the PDSI, it can be computed at almost any time scale and yet an extract more or less the same information contained by the temporally fixed PDSI, it has no theoretical upper or lower bounds, and it is easy to interpret.

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