African Journal of Agricultural Research Vol. 5(14), pp. 1784-1793, 18 July, 2010
Available online at http://www.academicjournals.org/AJAR
ISSN 1991-637X ©2010 Academic Journals

Full Length Research Paper

Using precipitation effectiveness variables in indexing drought in semi-arid regions

J. A. Otun

Department of Water Resources and Environmental Engineering, Ahmadu Bello University, Zaria, Nigeria.
E-mail: jotun@abu.edu.ng.

Accepted 26 June, 2010

This study proposes a new drought index based on several precipitation-based parameters to quantify drought hazard in semi arid region. In addition to the practice of using only rainfall volume for indexing drought, the proposed index verifies the potentials of nine other precipitation effectiveness variables (PEVs) onset of rain, cessation of rain, length of rainy and dry season, wet days and dry days within a wet season, dry days within the year, maximum dry spell length within a wet season and mean seasonal rainfall depth (MAR) in quantifying the drought conditions over a place. The conjunctive Precipitation Effectiveness Index (CPEI), as proposed in this study, utilizes a mathematical model, which algebraically combines "standardized seasonal PEV difference or deficit in each prevailing PEV" and terms of their sequent higher powers to define a single numerical value for this "at-site" drought index approach. Some statistical comparison tests were employed to determine the most appropriate set of PEV that can be employed in the CPEI model to quantify the drought conditions at each study location. The daily rainfall data obtained from seven synoptic stations in the semi-arid region of Nigeria were obtained, tested and then used to verify the effectiveness of this new method. Results obtained showed that the optimum no of PEVs that can be effectively combined to get the optimum CPEI values for indexing the drought in the study area is three PEVs for Gusau and Kano, five PEVs for Sokoto and Maiduguri and four for the rest stations under study. The trends observed in drought values obtained using the CPEI models employing these optimum PEVs also clearly earmarks the 1970 -73 and 1983 - 1987 historical drought years within the study area. This approach seems to be significant for the specific area in the Sudano-Sahelian Region of Nigeria but would need to be verified in a wider regional context in similar future study.

Key words: Drought indexing, precipitation effectiveness variables, semi arid regions.

INTRODUCTION

Up to date, rainfall-deficiency concepts and techniques are a larger proportion of the existing drought evaluation or quantification techniques in literature. Conceptually, these techniques have mainly used only 'rainfall amount' in their formulation and analysis. They have neglected the use of some other derived characteristics of rainfall that equally measure the effectiveness of rainfall occurrence over an area; and that also infer the occurrence of drought over such an area. Such "neglected" rainfall variables (referred to as Precipitation Effectiveness Variables (PEVs)) include rainfall features such as its timing (that is, onset and cessation of rainfall, length of rainy season), its availability (number of rainfall events and non rainfall events, (that is no of wet days, number of dry days), its frequency and distribution over a place (Otun, 2005).

The premise for developing an operational drought index using these PEVs is firstly due to the presumption that the PEVs give the first indication of drought over a place. Secondly, the inclusion of more than one of these PEVs for evaluating a drought index for a place is also on the basis that the salient aspect of drought characterization that would have been lumped if not entirely omitted or hidden by one PEV, may be better revealed or earmarked by another (Smakhtin and Hughes, 2004; Keyansh and Dracup, 2002; Oladipo, 1985). The inclusion of PEVs for indexing drought in semi-arid and arid regions (SAR) of the world is very significant in that in

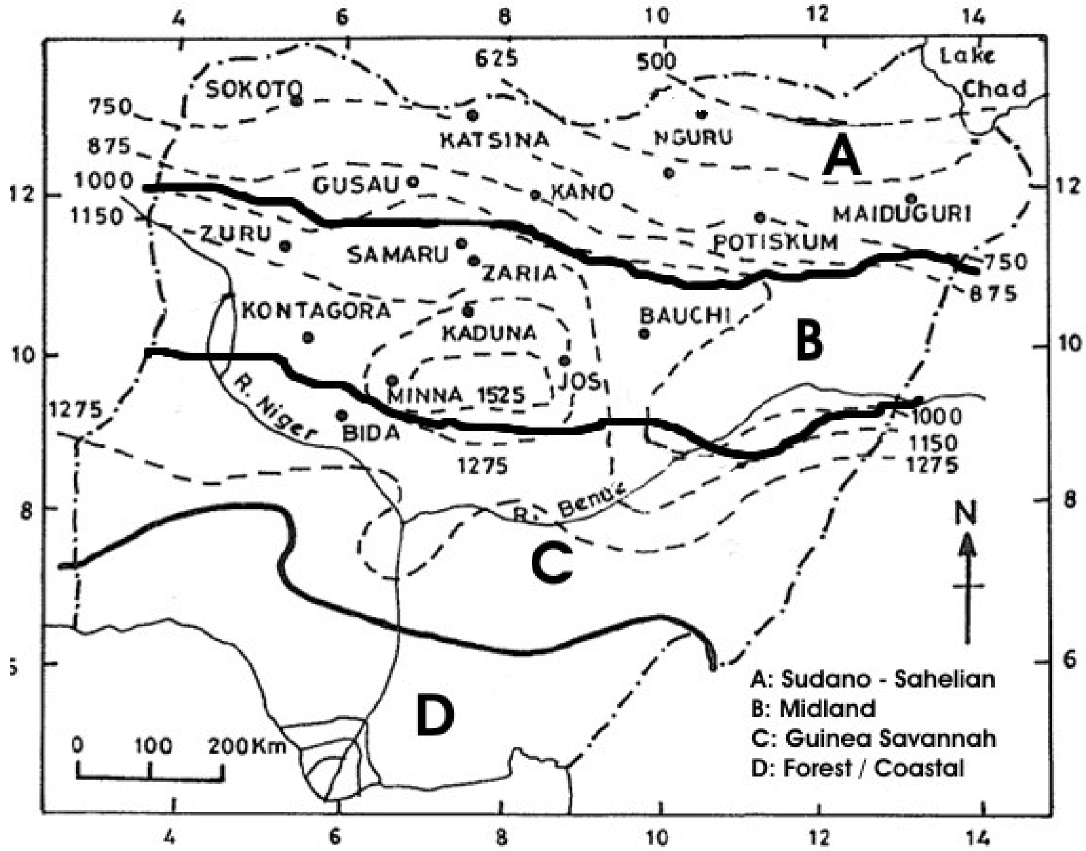

Figure 1. Map of Nigeria showing the Sudano-Sahelian region and the synoptic stations used in the study.

these regions, it is not so much the amount of rainfall that matters considering the arid nature of the area. What matters most is how effective it is. For instance, a delay in the onset of rains may result in poor seasonal distribution, even when the total amount of rainfall received within the same season is normal. Similarly, a pre-mature cessation may constitute a serious water deficit problem. A worse condition may be obtained when the onset is delayed and the rains ceases pre-maturely resulting in shortened rainy season.

This proposed approach conjunctively uses a combination of these PEVs to develop an operational drought index for quantifying the drought conditions over any semi-arid or arid region of the world. It is therefore hoped that this proposed drought quantification technique will serve as a reliable tool for better drought planning and management that can result in an effective management of the entire water resources systems of the SAR.

Study area

The area used for the study is the Sudano-sahelian region of Nigeria (SSRN). It is a semi-arid region that lies between latitudes 10° N – 14°N and longitudes 3° and 14.5° E as shown in Figure 1. Its climate results from the influence of two main wind systems: the moist, relatively cool, monsoon wind which blows from the Atlantic Ocean towards the country and brings rainfall; and the hot, dry, dust-laden Harmattan wind which blows from the north-east across the Sahara desert. The mean temperature in SSRN is generally between 25 and 35°C (Otun, 2005). Daily rainfall records used in this study are from seven well-spatially distributed synoptic stations shown in Figure 1. Detail information on each of these stations is shown in Table 1. These stations were managed by the Nigerian Meteorological Agency and each has continuous long term rainfall records. The available rainfall data for each meteorological station in SSRN was preliminary checked and found to be homogeneous and consistent using the double mass curve analysis. Stations having wide ranges of missing records and inconsistency in their records were excluded in the study. A list of years with such records that were exempted in the analysis for each station under study is also included in Table 1.

REVIEW OF INDEX-BASED DROUGHT QUANTIFICATION TECHNIQUES

The identification and quantification of droughts are achieved through analyses of time series of a drought

Table 1. Information on the meteorological stations used in the study.

S/No.	Station	Period of record used		Latitude	Longitude	Altitude (m)	Years with missing records (Exempted in the Analysis)
1	Gusau	1942	2002	12o 10‘ N	06° 42’ E	461	1995,1996,1997,1998,2000
2	Kano	1916	2003	12o 03‘ N	08° 32’ E	469	Nil
3	Katsina	1922	2003	13o 10‘ N	07° 41’ E	514	1925,32,43,44,45,46,47,48,1966,67,68,95,97
4	Maiduguri	1945	2003	11o 51‘ N	13° 05’ E	351	1949,1972,1981,1997
5	Nguru	1942	2001	12o 53‘ N	10° 28’ E	341	1961,1965,1986,1994, 1996
6	Potiskum	1936	2003	11o 22‘ N	11° 02’ E	412	1940,66,67,68,70,87,91,93
7	Sokoto	1952	2003	13o 10‘ N	05° 11’ E	348	1995

variable such as rainfall, groundwater levels, and soil moisture data, on a variety of time scales (Sharma, 2000; Tallaksen et al., 1997). Panu and Sharma (2002) gave the broad classification of all the methods used for characterizing or quantifying droughts to include the index-based methods, Frequency- or probability-based methods, Regression-based methods, Runs-based methods, and the Group-based method. Since the index-based methods, because of its simplicity in computation and widest applications, is the commonest and most robust technique used for quantifying meteorological drought, the proposed technique termed the conjunctive precipitation effectiveness index (CPEI) follows accordingly.

Basically, the index-based drought quantification methods integrate various hydro-meteorological parameters (obtained from data series of rainfall, evapotranspiration, streamflow and other water deficiency indicators) into a single number to provide an overview of drought in a region. The index obtained, usually used for decision making, defines the magnitude, duration or severities of droughts (Narasimhan, 2004; Hayes, 2002). The most commonly used of such meteorological drought indices include the Palmer Drought Severity Index (PDSI) (Palmer, 1965), Bhalme and Mooley Drought Severity Index (BMDI) (Bhalme and Mooley, 1980), Rainfall Anomaly Index (RAI) (Rooy, 1965), Reclamation Drought Index (RDI), Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982), and Standardized Precipitation Index (SPI) (McKee et al., 1993). The proposed CPEI is an index-based method aimed at quantifying meteorological drought over a place on a variety of time scale.

FORMULATION OF CPEI

The originality of the CPEI is related to the use of several precipitation-based parameters, not only precipitation amount for drought analysis and monitoring. The PEVs conjunctively used in CPEI include the following: onset of rainy season defined as the 1st day it rains in a season (ORS), cessation of rainy season defined as the last day it rains in a season (CRS), Length of the rainy season defined as the difference between CRS and ORS (LRS), Total wet days defined as the total number of days it rains within a season (TWD), Total number of dry spells within a season (TDS), Total number of dry days within a wet season (TDW), Total number of dry days within the whole season (TDY), Length of dry season (LDS), Maximum dry spell length within a wet season (MDL), and Mean seasonal rainfall depth (MAR). By redefining these PEVs, their standardized value is mathematically given in equation 1.

$$ {}_{k}SV_{l,j} = \frac{{}_{k}V_{l,j} - {}_{k}\bar{V}_{l,j}}{\sigma_{{}_{k}V_{j}}} \qquad (1) $$

Where k stands for the PEV variable under consideration (that is, for ORS, k =1, LRS, k = 2, LRS, k = 3 …., MDL, k = 9 and MAR, k = 10). l is the year under consideration, j is the season under consideration (for the monthly step data, j varies from 1 to 12 seasons, ${}_{k}\bar{V}_{l,j}$ and $\sigma_{{}_{k}V_{j}}$ are respectively the mean and standard deviation for the jth season and for variable k. By using Equation (1) the seasonality inherent in the PEVs can be removed and its values can be compared across various seasons.

Conceptually, the standardized difference value (${}_{k}SV_{l,j}$) and its higher powers for each PEVs is summed for the most suitable combination of PEVs to calculate CPEI for any year (l) or season (j) under consideration at any particular location. In formulating the model for CPEI in equation (2), the value of ${}_{k}SV_{l,j}$ was intentionally and respectively raised to the power of one, two and three so as to magnify the effect of the difference or deficit in the computation of the index. The sign ${}_{k}SGN$ was also included in the CPEI model, so as not to loose the effect of a negative difference (deficit) when it is squared or raised to higher power. Similarly, raising this standardized difference to a power of four or more has been proved to make little difference to the performance of the CPEI model (Otun, 2005).

$$CPEI_{l,j} = \tfrac{1}{3}\left(\left[\frac{1}{nv}\sum_{m=1}^{nv}\left({}_{k}SV_{l,j}\right) \right] + \left[\frac{1}{nv}\sum_{m=1}^{nv}\left({}_{k}SV_{l,j}\right)^{2} \left({}_{k}SGN\right) \right] + \left[\frac{1}{nv}\sum_{m=1}^{nv}\left({}_{k}SV_{l,j}\right)^{3} \right] \right) \quad (2)$$

Where nv is the no of PEVs in the arrangement, ${}_{k}SV_{l,j}$ is the standardized difference value and ${}_{k}SGN$ is the sign of the difference for the variable k.

By carrying out two comparative tests, the most appropriate PEVs combination for indexing the drought condition of any particular locality can be subjectively determined. The first test referred to as predictive-ability comparative test (PACT), uses some statistical procedures to compare the set of CPEI values obtained for various seasons and for each of the possible 1023 arrangements with the corresponding set of values obtained for each other three, four or five meteorological drought indices. This helps to determine the performance of each PEVs in the computation of CPEI and possibly serve as the clue in the preliminary elimination of some PEVs with poor performance.

After PACT, the sets of ‘well-performed’ PEVs will be used in the CPEI model and the values obtained will then be compared with their corresponding historical drought records to obtain the most appropriate PEVs and CPEI model for the locality under study. The “historical drought records of each station” refers to specific drought years where drought was historically recorded in the archives for the study area. This second test constitutes what is referred to as the descriptive-ability comparison test (DACT). It is a confirmatory test after that of PACT to cross check that the CPEI values obtained using a particular PEV combination for notable historical drought years have corresponding negative values. The optimum PEV combination is the one out of the “well-performed” PEVs that has more corresponding negative drought values for the historical drought years in archives.

Comparative analysis (CPEI versus BMDI, RAI and SPI)

As discussed, the initial step in PACT involves a preliminary comparison of CPEI values with those of three other meteorological drought indices, namely the BMDI, SPI and RAI. The detail procedures for computing these three drought indices has been fully described by Otun (2005), Smakhtina and Hughes (2004), Kenyantash and Dracup (2002) and Hayes (2002). The statistical tool used for comparing the performances of these indices with each other is the Pearson Correlation Coefficient (R).

CPEI model application and discussions

Using the available and homogeneous rainfall records between 1918 and 2002, for seven stations in the Sudano-Sahelian Region of Nigeria (SSRN), namely Gusau, Kano, Katsina, Maiduguri, Nguru, Potiskum and Sokoto, the CPEI values for each of the 1023 arrangements were computed and compared with the corresponding values obtained for BMDI, RAI and SPI.

The set of CPEI values for each of the possible 1023 arrangements was correlated with the set of corresponding values for BMDI, RAI and SPI indices. The arrangements with a correlation coefficient ($R > 0.8$) for each compared values of BMDI, RAI and SPI were selected. For each station under study, the total number of arrangements out of the possible 1023 arrangements with an average score of $R>0.8$ is shown in the first column of Table 2. (This procedure constitutes the 2nd stage of PACT). It is clear from Table 2 that a combination of more than seven PEVs was ineffective in indexing the drought in the SSRN. Using the maximum percentage of occurrence of the total variables as a criteria, the optimum number of PEVs for drought quantification in Gusau, Maiduguri and Potiskum is four, while the rest stations under study has five variables as their optimum. The frequency of occurrence of total variables observed with the use of three PEVs was also significant in most of the stations.

Table 2 also gives a clue as to how many PEVs should be used in indexing drought in each of the stations under study. Although not conclusive, Table 2 signifies that the use or a combination of three, four or five PEVs have a fair potential for indexing the drought in most of the stations under study.

Table 3 also gives the frequency of occurrence of each PEV in the lots of arrangements with average score R >0.8. At 50% level of occurrence, variables no 10 and 4 (that is, MAR and TWD) predominates in all the stations and at 40% level of occurrence, variables 10, 4, 8 and 1 (that is, MAR, TWD, LDS and ORS) becomes the most predominant variables. The average values of R obtained for the correlation of CPEI versus SPI, RAI and BMDI respectively for each station were ranked. The PEVs arrangement that was ranked first was assumed to give the optimum PEVs combination for computing the optimal CPEI. The ranking of some PEVs combinations used for indexing drought in the seven stations under study is shown in Tables 4a-g.

It is also clear from Tables 4a-g that the use of the entire 10 PEVs resulted in a very poor level of performance (in terms of R values) in all the stations under study. On the contrary, the use of PEV variable no 10, that is MAR proved to give the best performance in all

Table 2. Percentage distribution of total PEVs used to obtain CPEI with an average score (R> 0.8) in each station under study.

	Frequency of Occurrence of total variables Used to Score R > 0.8 (%)							
	NOC1	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Gusau	37	0.0	0.0	13.3	40.0	33.3	6.7	6.7
Kanoap	43	0.0	16.3	30.2	25.6	18.6	7.0	2.3
Katsina	54	1.9	13.0	27.8	22.2	25.9	7.4	1.9
Maiduguri	28	0.0	3.6	14.3	35.7	32.1	10.7	3.6
Nguru	65	4.6	16.9	29.2	24.6	15.4	6.2	3.1
Potiskum	60	3.4	22.0	23.7	25.4	20.3	3.4	1.7
Sokoto	64	4.7	17.2	31.3	25.0	17.2	3.1	1.6

1NOC – Total number of occurrence (that is, no of arrangements out of 1023 with average score R> 0.8).

Table 3. Performance level of each PEVs (%).

Station	MAR	MDL	LDS	TDY	TDW	TDS	TWD	LRS	CRS	ORS
	10	9	8	7	6	5	4	3	2	1
Gusau	100.0	13.3	46.7	20.0	20.0	0.0	73.3	40.0	0.0	33.3
Kanoap	100.0	14.0	48.8	20.9	27.9	37.2	79.1	44.2	4.7	46.5
Katsina	100.0	40.7	38.9	25.9	20.4	25.9	75.9	29.6	7.4	48.1
Maiduguri	100.0	21.4	28.6	28.6	3.6	46.4	71.4	14.3	0.0	42.9
Nguru	98.5	9.2	40.0	13.8	18.5	56.9	80.0	27.7	36.9	58.5
Potiskum	100.0	41.7	48.3	18.3	15.0	56.7	81.7	38.3	5.0	46.7
Sokoto	100.0	28.1	50.0	17.2	20.3	54.7	78.1	31.3	12.5	59.4

Table 4a. Ranking of each PEV combinations for Gusau.

Ranking	Serial No (Out of 1023)	Total variables	1Combined PEVs	Pearson correlation coefficient (R)			
				SPI	RAI	BMDI	Average
1	10	1	10	0.999	0.976	0.995	0.990
2	152	3	10,7,4	0.960	0.940	0.950	0.950
3	40	2	10,4	0.899	0.901	0.894	0.898
6	239	4	10,9,4,1	0.862	0.879	0.853	0.865
7	599	5	10,8,7,4,3	0.847	0.889	0.853	0.863
36	722	6	10,8,6,4,3,1	0.772	0.81	0.772	0.785
37	1023	10	10,9,8,7, 6,5,4,3,2,1	0.422	0.436	0.415	0.424

1 PEV Code (that is, 10 = MAR, 9 = MDL, 8 = LDS, etc.) are as defined in Table 2.

the stations under study. This is well expected since SPI, RAI and BMDI indices used for the comparisons also used only ‘rainfall depth’ like MAR for drought indexing. It may therefore be misleading to base the decision of how many PEVs to use on this result alone.

By comparing Table 2 and 4 (a-g), it may be seen that the CPEI values obtained by using a combination of three, four, or five PEVs respectively, has good rankings and highest frequency of occurrence in all the stations under study. The use of these variables has also resulted in high level of performance (average R > 0.9) in most stations under study. Similarly, by combining the predictive ability test results obtained above with the use of the Pearson Correlation coefficient (R) and that of a descriptive ability test; in which CPEI values obtained for these 3, 4 and 5 PEVs were plotted and compared with respective historical drought records of each stations (Figures 2 and 3), the following conclusion is put forward; as indicated on Table 5b, it is suggestive that a combination of three optimum PEVs (that is MAR, TDY

Table 4b. Ranking of each PEV combinations for Kano.

Ranking	Serial No. (Out of 1023)	Total variables	1Combined PEVs	Pearson correlation coefficient (R)			
				SPI	RAI	BMDI	Average
1	10	1	10	0.973	0.983	0.954	0.970
2	152	3	10,7,4	0.956	0.971	0.935	0.954
4	233	4	10,6,4,1	0.927	0.983	0.912	0.941
5	453	5	10,7,4,3,1	0.914	0.963	0.905	0.927
9	40	2	10,4	0.901	0.939	0.883	0.908
12	722	6	10,8,6,4,3,1	0.860	0.935	0.853	0.882
44	1023	10	10,9,8,7,6,5,4,3,2,1	0.606	0.662	0.590	0.619

1 PEV Code (that is, 10 = MAR, 9 = MDL, 8 = LDS, etc.) are as defined in Table 2.

Table 4c. Ranking of each PEV combinations for Katsina

Ranking	Serial No. (Out of 1023)	NOV	1Combined PEVs	Pearson correlation coefficient (R)			
				SPI	RAI	BMDI	Average
1	10	1	10	0.999	1.000	1.000	1.000
2	152	3	10,7,4	1.000	1.000	1.000	1.000
3	453	5	10,7,4,3,1	0.935	0.943	0.944	0.941
5	40	2	10,4	0.929	0.939	0.941	0.937
6	239	4	10,9,4,1	0.922	0.928	0.931	0.927
19	751	6	10,9,7,5,4,1	0.866	0.864	0.865	0.865
55	1023	10	10,9,8,7, 6,5,4,3,2,1	0.550	0.542	0.542	0.545

1 PEV Code (that is, 10 = MAR, 9 = MDL, 8 = LDS, etc.) are as defined in Table 2.

Table 4d. Ranking of each PEV Combinations for Maiduguri.

Ranking	Serial No. (Out of 1023)	Total variables	1Combined PEVs	Pearson correlation coefficient (R)			
				SPI	RAI	BMDI	Average
1	10	1	10	0.995	1.000	1.000	0.998
2	152	3	10,7,4	0.993	0.999	1.000	0.997
3	40	2	10,4	0.936	0.915	0.944	0.932
6	239	4	10,9,4,1	0.881	0.866	0.889	0.879
14	483	5	10,7,5,4,1	0.837	0.836	0.858	0.844
18	751	6	10,9,7,5,4,1	0.841	0.829	0.848	0.839
29	1023	10	10,9,8,7,6,5,4,3,2,1	0.359	0.352	0.341	0.351

1 PEV Code (that is, 10 = MAR, 9 = MDL, 8 = LDS, etc.) are as defined in Table 2.

and TWD) can be used for indexing the drought in Gusau and Kano, combination of five optimum PEVs for Katsina and Sokoto and a combination of four PEVs for the rest stations under study. The usual use of only rainfall depth that is one PEV in indexing the drought in the study area might be elusive since some other distinctive drought features revealed with the use of three, four and five PEVs in Figures 2 and 3 might have remained hidden.

Table 5 shows the results of the most suitable PEV combinations suggested for each station under study. It is obvious from these results that other PEVs apart from rainfall volume can be used to index the drought condition of a location. However, it should also be stated that the emphasis of this study was not in the formulation of a ‘one-in-all’ index but rather seek to prove that more PEVs can be included in drought index formulation for a semi-arid/arid regions of the world. This study has used equation 2 as a model sample. Therefore, this study

Table 4e. Ranking of each PEV combinations for Nguru.

Ranking	Serial No (Out of 1023)	Total variables	1 Combined PEVs	Pearson correlation coefficient (R)			
				SPI	RAI	BMDI	Average
1	10	1	10	1.000	1.000	1.000	1.000
2	152	3	10,7,4	1.000	0.988	0.996	0.995
3	40	2	10,4	0.973	0.968	0.977	0.973
4	209	4	10,4,3,1	0.936	0.929	0.934	0.933
12	455	5	10,8,4,3,1	0.878	0.875	0.877	0.877
29	716	6	10,8,5,4,3,1	0.853	0.847	0.848	0.849
66	1023	10	10,9,8,7, 6,5,4,3,2,1	0.361	0.380	0.379	0.374

1 PEV Code (that is, 10 = MAR, 9 = MDL, 8 = LDS, etc.) are as defined in Table 2.

Table 4f. Ranking of each PEV combinations for Potiskum.

Ranking	Serial No (Out of 1023)	Total variables	1Combined PEVs	Pearson correlation coefficient (R)			
				SPI	RAI	BMDI	Average
1	10	1	10	0.994	1.000	1.000	0.998
2	152	3	10,7,4	0.994	1.000	1.000	0.998
3	40	2	10,4	0.938	0.949	0.948	0.945
4	233	4	10,6,4,1	0.915	0.924	0.923	0.921
8	453	5	10,7,4,3,1	0.897	0.900	0.900	0.899
16	845	6	10,9,8,7,5,4	0.879	0.886	0.885	0.884
61	1023	10	10,9,8,7, 6,5,4,3,2,1	0.533	0.530	0.530	0.531

1 PEV Code (that is, 10 = MAR, 9 = MDL, 8 = LDS, etc.) are as defined in Table 2.

Table 4g. Ranking of each PEV combinations for Sokoto.

Ranking	Serial No. (Out of 1023)	Total variables	1Combined PEVs	Pearson correlation coefficient (R)			
				SPI	RAI	BMDI	Average
1	10	1	10	1.000	1.000	1.000	1.000
2	152	3	10,7,4	1.000	1.000	1.000	1.000
3	453	5	10,7,4,3,1	0.944	0.965	0.971	0.960
5	40	2	10,4	0.944	0.957	0.961	0.954
6	233	4	10,6,4,1	0.938	0.950	0.954	0.947
12	752	6	10,9,8,5,4,1	0.900	0.909	0.914	0.908
65	1023	10	10,9,8,7, 6,5,4,3,2,1	0.575	0.604	0.606	0.595

1 PEV Code (that is, 10 = MAR, 9 = MDL, 8 = LDS, etc.) are as defined in Table 2.

should be regarded as a preliminary approach to drought quantification using PEVs. More research would be required for the development of a scientifically proved model for indexing drought using the suggested PEVs. Similarly, a further research would be required to determine the various weights to use for each of these PEVs in model formulation since some variables could be more important for drought quantification than the others.

Conclusion

A new drought indexing method, CPEI, using PEVs has been proposed for quantifying the drought conditions and occurrences in any semi-arid or arid region. It is a pioneering approach that has shown that drought indexing in these regions is related to the use of several characteristics of precipitation and not only precipitation

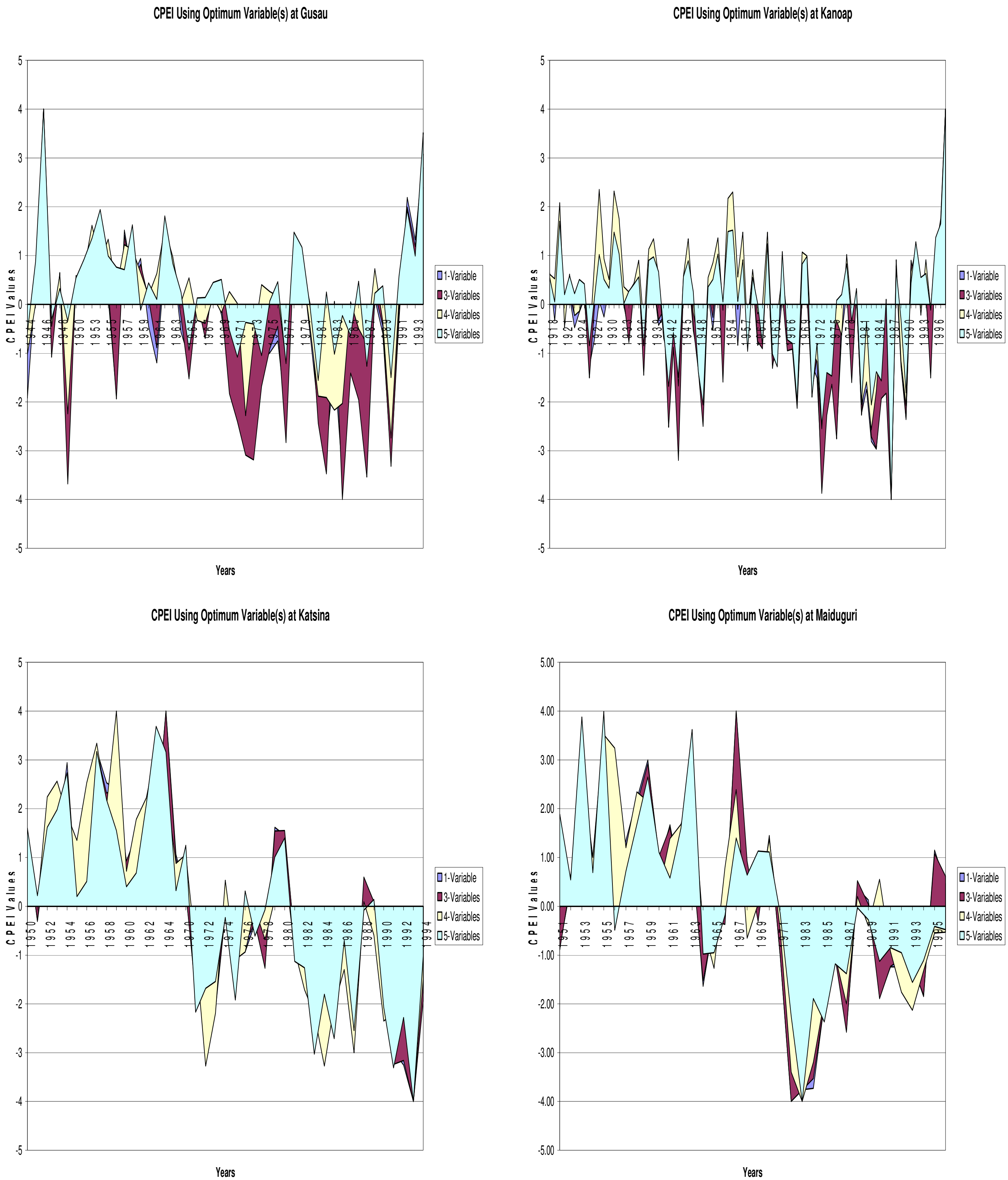

Figure 2. Comparison of Optimum CPEI obtained using 1, 3, 4, and 5 PEVSs at Gusau, Kano, Katsina and Maiduguri stations.

Table 5. Suggested PEV combinations for indexing drought in each station under study.

Station	Optimum No. of PEV	Suggested PEV combination (codes)	Suggested PEV combination
Gusau	3	10,7,4	MAR, TDY, TWD
Kanoap	3	10,7,4	MAR, TDY, TWD
Katsina	5	10,7,4,3,1	MAR, TDY, TWD, LRS, ORS
Maiduguri	4	10,9,4,1	MAR, MDL, TWD,ORS
Nguru	4	10,4,3,1	MAR, TWD, LRS,ORS
Potiskum	4	10,6,4,1	MAR, TDW, TWD,ORS
Sokoto	5	10,7,4,3,1	MAR, TDY, TWD, LRS, ORS

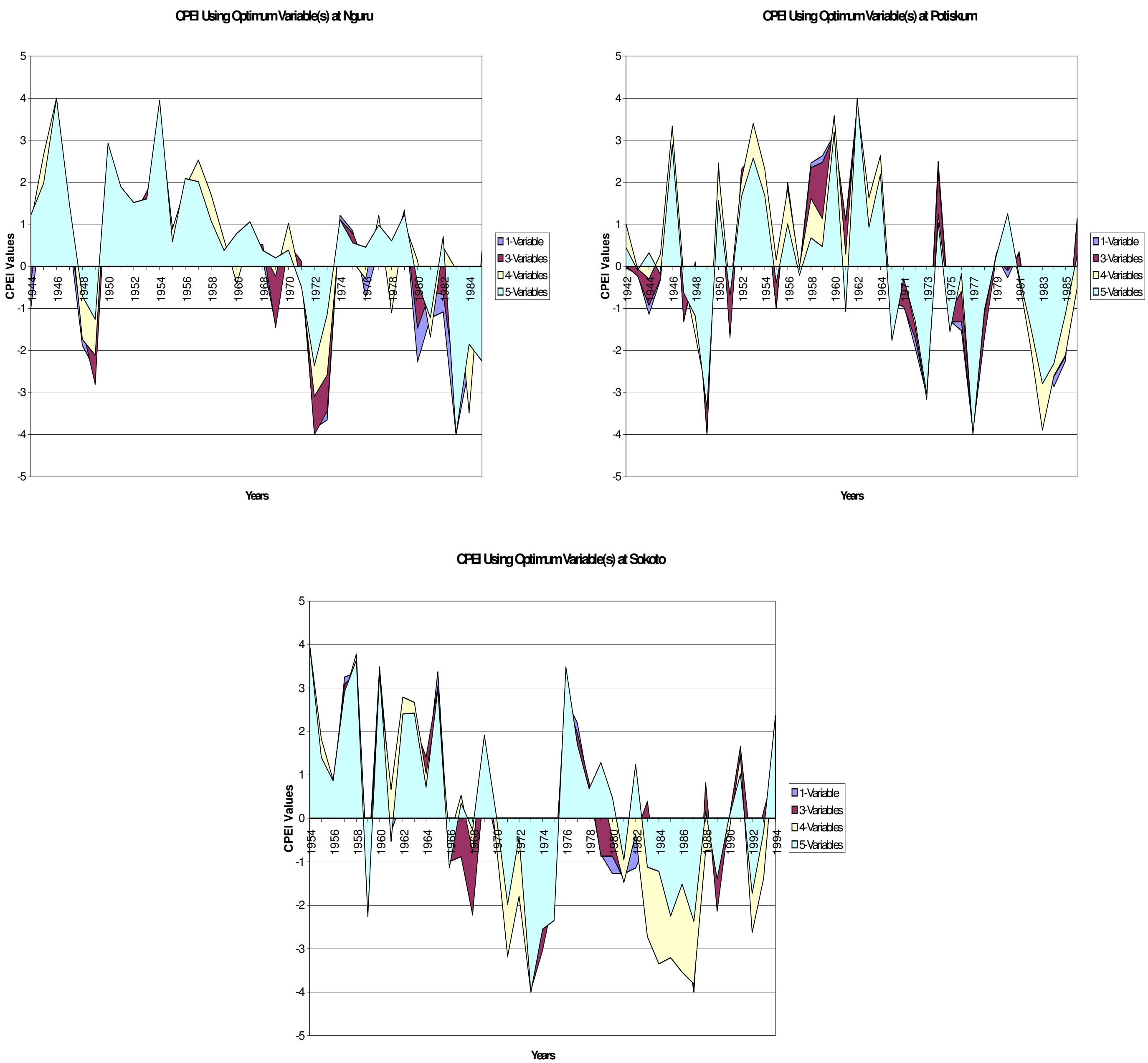

Figure 3. Comparison of Optimum CPEI obtained using 1, 3, 4, and 5 PEVSs at Nguru, Potiskum and Sokoto station.

amount. The application of CPEI can be applied to at-site specific drought evaluation studies.

ACKNOWLEDGEMENTS

The author acknowledged the role played by late Dr. L. I. O. Odigie and the Management of Ahmadu Bello University, Zaria (Nigeria), the sponsor, of this research study.

REFERENCES

Bhalme HN, Mooley DA (1980). Large-scale drought / flood and monsoon circulation: Mon. Weath. Rev., 108: 1197.

Hayes M (2002). Drought indices, 9-page on-line document at http:// www.drought.unl.edu/whatis/indices.pdf, last assessed August, 2002.

Keyanash JA, Dracup JA (2002). The quantification of drought: An evaluation of drought indices: Bulletin of the Am. Meteorol. Soc., 83(8): 1176-1180.

McKee TB, Doesken NJ, Kleist NJ (1993). The relationship of drought frequency and duration to time scales. Proceedings, 8th Conference on Applied Climatology, 17-22 January, Anaheim, CA, pp. 179-184.

Narasimhan B (2004). Development of Indices for Agricultural Drought Monitoring using a spatially distributed hydrologic model. PhD. Thesis, Texas A&M University, College station USA, p. 187.

Oladipo EO (1985). A comparative performance analysis of three meteorological drought indices: J. Climatol., 5: 655-664.

Otun JA (2005). Analysis and Quantification of Drought Using Meteorological Indices in The Sudano-Sahel Region of Nigeria, Unpublished PhD Thesis, Ahmadu Bello University, Zaria, Nigeria.

Palmer WC (1965). Meteorological drought, Tech. Research paper U.S. Weather Bureau, US Dept. of Commerce, Washington, DC USA., pp. 45: 1-58.

Panu US, Sharma TC (2002). Challenges in drought research: some Perspectives and future directions. Hydrological Sciences Special Issue: Towards Integrated Water Res. Manage. Sustainable Dev., 47(S): S19-S30.

Rooy MP van (1965). A rainfall anomaly index, independent of time and space, Notos 14: 43-48.

Shafer BA, Dezman LE (1982). Development of a Surface Water Supply Index (SWSI) to assess the severity of drought conditions in snowpack runoff areas. Proceedings of the Western Snow Conference, pp. 164-175.

Sharma TC (1997). A drought frequency formula. Hydrol. Sci. J., 42(6): 803-814.

Sharma TC (2000). Drought parameters in relation to truncation levels. Hydrol. Processes, 14: 1279-1288.

Smakhtina VU, Hughes DA (2004). Review, automated estimation and analyses of drought indices in South Asia. Working Paper 83. Colombo, Sri Lanka: International Water Management Institute., p. 24.

Tallaksen LM, Madsen H, Clausen B (1997). On the definition and modeling of streamflow deficit duration and deficit volume. Hydrol. Sci. J., 42(1): 15-33.