Anatomy of a Rainfall Index

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ABSTRACT

One particular index has been commonly used to monitor precipitation in drought-prone regions such as the West African Sahel and the Brazilian Northeast. The construction of this index involves standardizing the annual total rainfall for an individual station and then averaging these standardized rainfall deviations over all the stations within the region to obtain a single value. Some theoretical properties of this "Standardized Anomaly Index" are derived. By studying its behavior when applied to actual rainfall data in the Sahel, certain aspects of the practical utility of the index are also considered. For instance, the claim that the Sahel has recently experienced a long run of relatively dry years does not appear to be sensitive to the exact form of index that is employed. On the other hand, it is shown by means of principal components analysis that no single index can "explain" a large portion of the variation in Sahelian rainfall, implying that much information, that is at least potentially useful, is lost when one relies only on a single index. The implications of these results for assessments of the impact of drought on society in arid and semiarid regions are discussed.

1. Introduction

In monitoring the duration and intensity of drought over an entire region, it is convenient to make use of an index that encapsulates the spatial pattern of the incidence of drought in terms of a single number. Such an index is used not only by scientists, but also by individuals charged with, for example, monitoring climatic conditions for the purpose of identifying when crop production has declined and as a result drought relief might be needed.

An index can be potentially very useful, if its statistical characteristics are properly understood. If suitably constructed, it provides a single representative number for a given region, a number that can be easily monitored for changes over time, a major simplification over being required to simultaneously study data for several locations within the region. Yet, if its limitations are not well understood by the user, there is the danger that an index might be misused in the desire, for example, to have an "objective," scientifically based triggering device for emergency drought assistance, such as that proposed by Mayer (1985).

One particular index has been commonly used to monitor precipitation in drought-prone regions such as the West African Sahel (Kraus, 1977; Katz, 1978; Lamb, 1982, 1983; Nicholson, 1983) and the Brazilian Northeast (Hastenrath, 1984; Hastenrath et al., 1984). The construction of this index involves standardizing the annual (or seasonal) total rainfall for an individual station by subtracting the station's mean and dividing by its standard deviation, with the mean and standard deviation being computed from the station's historical record. These standardized rainfall deviations (or anomalies) are then averaged over all the stations within the region to obtain a single annual (or seasonal) value for the index. For clarity, this index shall be referred to as the "Standardized Anomaly Index." Although it has been argued that this Standardized Anomaly Index is intended to be employed solely as a convenient device in climatological research, the index has in fact been relied on in popular articles, for instance, to "document" that the Sahel is currently experiencing a drought that has persisted for at least 15 years (Kerr, 1985).

Little or no justification for the use of the Standardized Anomaly Index, however, has been provided, nor have its properties been examined. In this paper, some theoretical properties of the Standardized Anomaly Index are presented (section 2). By studying its behavior when applied to actual rainfall data in the Sahel, certain aspects of the practical utility of the Standardized Anomaly Index are also considered (section 3). For instance, the sensitivity of the claim that the Sahel has recently experienced a long run of relatively dry years to the exact form of index that is employed (i.e., method of standardization, number of stations considered, etc.) is determined. Further, by means of principal components analysis, the amount of information (at least potentially useful) that is lost when one relies only on a single index is quantified. The implications of these results for assessments of the impact of drought on

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society in arid and semiarid regions are discussed (section 4). We note that Wigley et al. (1984) have conducted a closely related study on the effects of spatially averaging fields of climatic data.

2. Theoretical properties of Standardized Anomaly Index

Before considering the formal definition and properties of the Standardized Anomaly Index, it is necessary to mention what statistical properties would be desirable in almost any conceivable circumstances. It is convenient to regard an index as a random variable with an underlying, possibly unknown, probability distribution. If the expected value (mean) of this distribution is known, then the index can be redefined so that its expected value equals a given value (e.g., zero). If the variance of the distribution is known, then the index can be redefined so that its variance can be taken equal, for instance, to unity. Ideally, knowledge of the functional form of the entire probability distribution of an index would be useful. Determining the expected value of an index is generally straightforward, whereas determining the variance is somewhat more difficult, and determining the exact probability distribution is frequently impossible. Requiring the index to have fixed expected value and variance is desirable in order to make comparisons of index values (e.g., among different regions) meaningful.

a. Definition

Assume that time series of total rainfall (e.g., on an annual basis) are available at N sites within a region and let the random variable R_{it} denote the total rainfall during the tth time period at the ith station. The Standardized Anomaly Index used by Kraus (1977) and others is viewed as a random variable I_t whose value for the tth time period is given by

$$I_t = \frac{1}{N} \sum_{i=1}^{N} (R_{it} - \mu_i)/\sigma_i. \tag{1}$$

Here the parameters μ_i and σ_i denote, respectively, the population mean (or expected value) and the standard deviation of the total rainfall at the ith station; that is,

$$\mu_i = \int_0^\infty x \, dF_i(x),$$

$$\sigma_i^2 = \int_0^\infty (x - \mu_i)^2 \, dF_i(x), \tag{2}$$

where F_i denotes the distribution function for the ith station (i.e., for R_{it}).

Conceptually, the Standardized Anomaly Index involves the conversion of the observed rainfall at a station into units, the number of standard deviations from the long-term station mean. These station standard deviations from the mean (i.e., standardized anomalies) are then averaged to obtain a single index value. For simplicity, several assumptions will be made here about the parameters that appear in (1). The station population means (μ_i) and standard deviations (σ_i) are taken to be known, whereas in practice these parameters are unknown and need to be estimated from the available number of rainfall observations for the sites [an especially limited number in the case of the Sahel (see section 3)]. This assumption makes the derivation of certain properties of the Standardized Anomaly Index simpler; however, most of these properties still hold either exactly or approximately when parameter estimates are substituted in (1). It will be tacitly assumed that the parameters μ_i and σ_i do not vary with the time period t; that is, that the station rainfall time series constitute realizations of stationary stochastic processes. This requirement implies that no real change in climate is taking place, an assumption that is quite useful at least as a baseline case in many analyses of rainfall data.

b. Interpretation

One alternative interpretation of this index will be discussed. Equation (1) can be re-expressed as

$$I_t = \frac{1}{N} \sum_{i=1}^{N} w_i R_{it} - c, \tag{3}$$

where $w_i = 1/\sigma_i$ and c is a constant involving the number of stations N, the population means (μ_i), and the population standard deviations (σ_i). In other words, the index I_t can be viewed as a weighted average (or linear combination) of the rainfall for the N stations, with the weights being inversely proportional to the station standard deviations. Although this weighting scheme may appear to be reasonable, it has a somewhat unexpected effect in practice. Ordinarily, as will be seen in the Sahelian rainfall example in section 3a, sites with higher mean rainfall tend to also have higher standard deviations. So (3) results in weighting the drier stations more [i.e., larger w_i in (3)] than the wetter stations.

c. Moments

Because the Standardized Anomaly Index involves deviations from the individual station means, its population mean is necessarily zero; that is,

$$E(I_t) = 0, \tag{4}$$

where "E" denotes the expectation operator. Thus, this index does meet the first goal of possessing an expected value (i.e., zero) that is invariant under any changes in the locations on which the index is based. In general, the variance of the Standardized Anomaly Index depends upon the spatial correlations among the rainfall at the N sites. Substitution into the general expression for the variance of a linear combination of correlated random variables (e.g., Hogg and Craig, 1970, p. 168) gives

$$\mathrm{var}(I_t) = \frac{1}{N} + \left(1 - \frac{1}{N}\right)\bar{\rho}. \tag{5}$$

Here

$$\bar{\rho} = \frac{1}{N(N-1)/2} \sum_{i<j} \rho_{ij}$$

with ρ_{ij} being the correlation between the ith and jth sites, and "var" denotes variance. If all of the sites are uncorrelated (i.e., $\rho_{ij} = 0$ for all i and j), then (5) reduces to

$$\mathrm{var}(I_t) = \frac{1}{N}. \tag{6}$$

If all of the sites are perfectly correlated (i.e., $\rho_{ij} = 1$ for all i and j), then (5) reduces to

$$\mathrm{var}(I_t) = 1. \tag{7}$$

The method of standardization used in (1) does not achieve unit variance, except in the special case (which never occurs in reality for fields of rainfall data or other climatological variables) of perfect correlation. In general, the variance of the Standardized Anomaly Index depends on the number of stations N. Thus, this index does not meet the second goal of possessing a variance that is invariant under any changes in the locations on which the index is based. In particular, it is not at all clear how best to adjust the index in the event that data were missing.

d. Probability distribution

Because the Standardized Anomaly Index involves a sum and because of the spatial correlation of rainfall, the exact probability distribution of this index is a complicated function that involves the N-dimensional joint distribution of station rainfall. In particular, if the joint distribution of rainfall totals at the N stations were multivariate Gaussian, then the probability distribution of the index I_t would also be Gaussian with mean zero and variance that depends on the spatial correlations (see section 2c) (e.g., Lindgren, 1968, p. 366). Station rainfall totals actually have a distribution that is positively skewed (especially in arid and semiarid regions, Katz and Glantz, 1977) and only becomes approximately Gaussian as the length of the time period t increases. But the averaging involved in (1) makes the distribution of the index I_t closer to Gaussian, being less skewed than those at the individual sites.

e. Autocorrelation

Rainfall time series for individual stations typically exhibit small positive autocorrelations. Since this quantity is sometimes taken as a measure of predictability and since it affects the properties of related quantities such as time averages of the index or cross correlations between the index and other (e.g., atmospheric) variables, it is of interest to compare these station autocorrelations with the autocorrelation for the Standardized Anomaly Index. Such a relationship is difficult to derive, because it essentially requires a multiple time series model for the joint behavior of the rainfall at the N sites. Some theoretical results for the special case of $N = 2$ stations are mentioned for illustrative purposes.

A general expression for the first-order population autocorrelation coefficient [$\rho_I(1)$ say] of the index I_t when $N = 2$ is given by

$$\rho_I(1) = \frac{\rho_1(1) + \rho_{12}(1) + \rho_{12}(-1) + \rho_2(1)}{2[1 + \rho_{12}(0)]}. \tag{8}$$

Here

$$\begin{aligned} &\rho_I(1) = \mathrm{corr}(I_t, I_{t+1}), \qquad \rho_1(1) = \mathrm{corr}(R_{1t}, R_{1,t+1}), \\ &\rho_2(1) = \mathrm{corr}(R_{2t}, R_{2,t+1}), \quad \rho_{12}(0) = \mathrm{corr}(R_{1t}, R_{2t}), \\ &\qquad \rho_{12}(1) = \mathrm{corr}(R_{1t}, R_{2,t+1}), \\ &\qquad \rho_{12}(-1) = \mathrm{corr}(R_{1t}, R_{2,t-1}), \end{aligned} \tag{9}$$

where "corr" denotes the population correlation coefficient. Specifically, $\rho_1(1)$ and $\rho_2(1)$ denote the first-order population autocorrelation coefficients for the two individual station time series of annual rainfall R_{1t} and R_{2t}, $\rho_{12}(0)$ denotes the contemporaneous population cross correlation coefficient between the two rainfall time series (denoted more simply as ρ_{12} in section 2c where leading and lagging were not considered), and $\rho_{12}(1)$ [$\rho_{12}(-1)$] denotes the population cross correlation coefficient when the first station time series leads (lags) the second station by one year.

It might be reasonable to assume that the two individual rainfall time series are both generated by first-order autoregressive processes (e.g., Box and Jenkins, 1976, p. 56) and that there is only a contemporaneous relationship (i.e., no leading or lagging) between the two time series in a predictive sense (e.g., Katz, 1985). In this case, the first-order autocorrelation coefficient for the Standardized Anomaly Index is simply the average of the two station autocorrelations; that is, (8) reduces to

$$\rho_I(1) = \tfrac{1}{2}[\rho_1(1) + \rho_2(1)]. \tag{10}$$

f. Alternative indices

In considering the properties of the Standardized Anomaly Index, the question of whether any other simple indices could be constructed that possess more desirable properties naturally arises. Although the answer to this question is not clearcut, the results in the preceding subsections suggest several alternative indices. The representation of the index I_t as a weighted average (3), for instance, suggests that different weighting schemes might be considered. The simplest weighting scheme is that of equal weights, or the ordinary spatial average, which has a somewhat simpler interpretation than the Standardized Anomaly Index.

Alternatively, the weights that are "optimal" according to a specified criterion could be determined. If the criterion of maximizing variance "explained" is adopted, then the so-called first principal component is the optimal weighted average (e.g., Anderson, 1958, p. 272). This first principal component, commonly employed in the statistical analysis of fields of climatic data, can be treated as a standard of comparison for the Standardized Anomaly Index. If all of the correlations between the pairs of stations are equal, say,

$$\rho_{ij} = \rho > 0 \quad \text{for all } i \text{ and } j,$$

then the first principal component (based on the correlation matrix) is identical to the Standardized Anomaly Index (Anderson, 1958, p. 287). In this case, the proportion of the total variance explained by the first principal component is

$$\frac{1}{N} + \left(1 - \frac{1}{N}\right)\rho,$$

or precisely the same as the expression (5) for the variance of the index I_t. More generally (i.e., when the pairwise correlations are not all identical), the first principal component differs from the Standardized Anomaly Index and explains a greater fraction of the total variance than does I_t. Note that since the maximum possible value of the variance of the Standardized Anomaly Index is unity in the case of perfect correlation (7), the general expression (5) always can be interpreted as the proportion of the total variance explained by the index.

3. Application of Standardized Anomaly Index to Sahel rainfall

In this section the behavior of the Standardized Anomaly Index when applied to some actual rainfall data in the Sahel is studied. Rainfall measurements totaled over the period April–October (which includes the entire wet season and is virtually the same as the annual totals) for 20 West African stations, located west of 9°E between 11° and 18°N, are considered. When individual station rainfall observations are missing, an adjustment is made to (1) as discussed by Kraus (1977). This adjustment involves replacing the divisor N by the number of the stations actually available and, in effect, taking rainfall for the missing stations to be average.

Table 1 lists the stations, as well as their sample means and standard deviations, and Fig. 1 includes their locations. Figure 2 shows a plot of the Standardized Anomaly Index for the time period 1941–81. A run of near or below zero values is evident since 1970. This rainfall index time series is essentially the same as that which appeared in Lamb (1982). The only difference is that the station means and standard deviations are estimated from the entire time period, whereas Lamb's parameter estimates are based only on observations through 1974.

a. Interpretation

Recalling the representation of the Standardized Anomaly Index as a weighted average (3), the relative

TABLE 1. Rainfall statistics for stations used to construct Standardized Anomaly Index for the Sahel.

Station	Latitude	Longitude	Number of years record*	Mean* (mm)	Standard deviation* (mm)
Bathurst, Gambia	13.28°N	16.39°W	41	1121	303
Bamako, Mali	12.40°N	7.59°W	41	1039	185
Gao, Mali	16.19°N	0.09°W	40	240	69
Kayes, Mali	14.26°N	11.28°W	40	722	153
Mopti, Mali	14.29°N	4.10°W	41	522	131
Tombouctou, Mali	16.49°N	2.59°W	32	200	81
Nema, Mauritania	16.32°N	7.12°W	39	283	81
Nouakchott, Mauritania	18.09°N	15.58°W	39	110	63
Agadez, Niger	17.00°N	7.56°E	38	152	68
Birni n'Konni, Niger	13.49°N	5.19°E	31	569	143
Niamey, Niger	13.32°N	2.05°E	41	572	144
Zinder, Niger	13.46°N	8.58°E	41	497	142
Kano, Nigeria	12.00°N	8.31°E	40	802	165
Bissau, Guinea-Bissau	11.52°N	15.39°W	40	1852	381
Dakar, Senegal	14.38°N	17.27°W	41	495	201
Podor, Senegal	16.35°N	15.02°W	41	279	121
St. Louis, Senegal	16.01°N	16.30°W	41	302	116
Tambacounda, Senegal	13.45°N	13.40°W	41	873	187
Bobo Dioulasso, Burkina Faso	11.11°N	4.18°W	40	1095	206
Ouagadougou, Burkina Faso	12.20°N	1.40°W	40	847	162

* April–October, 1941–81.

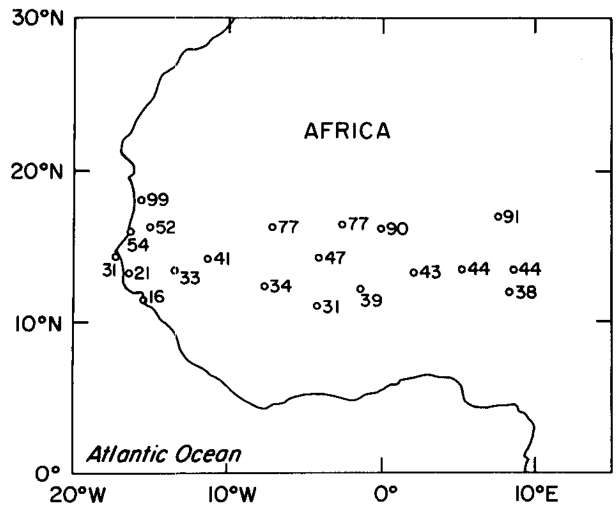

FIG. 1. Location of stations used to construct Standardized Anomaly Index for the Sahel. Numbers indicated on the map are the weights (times one thousand) that this index applies to each station.

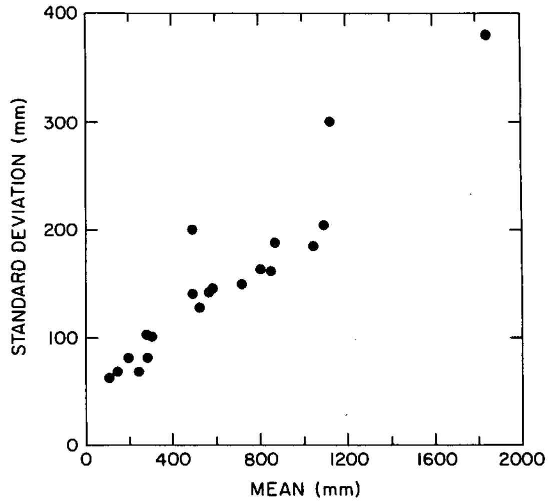

FIG. 3. Sample standard deviation versus mean of April–October rainfall during 1941–81 for each of the 20 stations listed in Table 1.

weighting of the 20 Sahel stations is considered. Figure 3 shows a plot of the station sample standard deviations ($\hat{\sigma}_i$) versus the station sample means ($\hat{\mu}_i$), confirming the remark made in section 2b that rainfall variability (in an absolute sense) tends to increase as the mean increases. Thus the sites that are drier on the average will tend to receive the most weight [i.e., largest w_i in (3)]. Figure 1 includes these weights on a scale normalized to sum to one. In particular, the station with the lowest mean (110 mm), Nouakchott, Mauritania, receives the highest weight (0.099), whereas the station with the highest mean (1852 mm), Bissau, Guinea-Bissau, receives the lowest weight (0.016). Although weighting one station more than six times greater than another may well be justified on a statistical basis, it may be difficult to explain on a practical basis to users of the index (especially nonscientists).

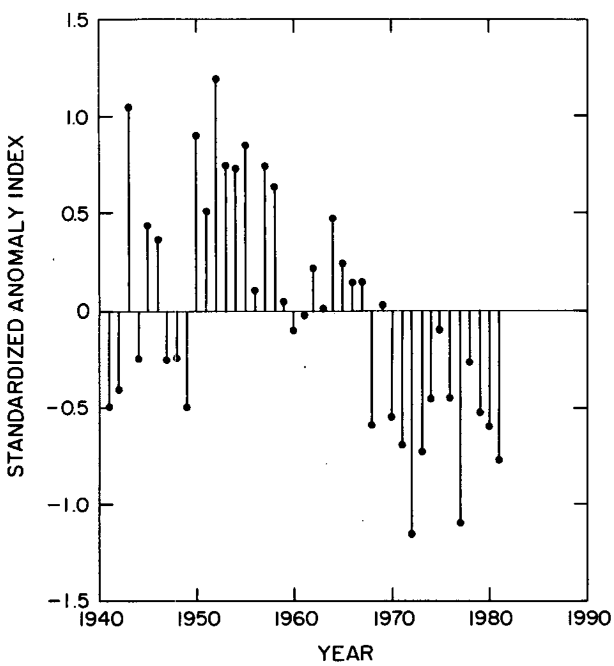

FIG. 2. Time series of Standardized Anomaly Index for the Sahel based on April–October rainfall during 1941–81 for the 20 stations listed in Table 1.

b. Moments and distribution

Because the sum of deviations about the sample mean is constrained to equal zero, the sample mean of the Sahel rainfall index time series (Fig. 2) necessarily equals zero, a property analogous to (4). The sample variance of the index I_t equals about 0.35, or roughly 37% of the way between the case of no spatial correlation [$\mathrm{var}(I_t) = 0.05$ by (6)] and perfect correlation [$\mathrm{var}(I_t) = 1$ by (7)]. This variance corresponds to an average pairwise correlation of $\bar{\rho} = 0.32$ in (5). The 190 [$=N(N-1)/2$] correlations between pairs of stations vary irregularly about this average value, with values ranging from virtually zero in several cases to as large as 0.72. The probability distribution of the Standardized Anomaly Index for the Sahel, as judged by a histogram, is approximately Gaussian. Apparently, the positive skewness that is characteristic of distributions of rainfall in arid and semiarid regions has been almost entirely removed by the process of totaling over the wet season and averaging over the 20 stations.

c. Autocorrelation

The sample first-order autocorrelation coefficient for the index I_t equals about 0.50, and an appropriate model for the autocorrelations (based on fitting low-order autoregressive processes) appears to be a first- or second-order autoregressive process. Because the sample first-order autocorrelation coefficients for the individual time series are quite close to zero (between 0 and 0.3 for most stations), this relatively substantial value of the autocorrelation for the index I_t is somewhat surprising. If there were no leading or lagging between station rainfall time series, a reasonable assumption when dealing with rainfall on an annual time scale, then (10) suggests that $\rho_I(1)$ should be relatively small. Closer examination of the rainfall time series for the individual stations reveals a weak tendency for positive "feedback" relationships (i.e., both leading and lagging being simultaneously present) (e.g., Granger and Newbold, 1977, p. 215); that is, the cross correlations when station i either leads or lags station j by one year, namely $\rho_{ij}(1)$ and $\rho_{ij}(-1)$, both tend to be positive, but small in magnitude. The relation (8), when generalized to $N > 2$ stations, is then sufficient to explain the apparent inflation of $\rho_I(1)$ over that expected based on (10). Of course, it remains unclear whether such feedback relationships are really present among the station rainfall time series. One popular alternative explanation (e.g., Winstanley, 1985) is that the Sahel has experienced a climatic "change," so that the apparent high autocorrelation is really indicative of nonstationarity and would disappear if this trend were removed.

d. Alternative indices

Alternative rainfall indices were constructed for the Sahel to see whether their behavior is consistent with that for the Standardized Anomaly Index. Equally weighted, ordinary spatial means and averages over fewer stations (to represent more homogeneous climatic regions) were considered. None of these changes has any substantial effect on the general characteristics of the time series produced. In particular, the marked dry period since 1970 is always evident, although whether a continuous run of below normal years has occurred does depend on the exact form of index and data.

Principal components analysis was performed using the correlation matrix for the 20 West African Sahel stations to identify the "optimal" rainfall index. The first principal component explains about 37% of the total variance, whereas the Standardized Anomaly Index explains about 35% of the total variance [namely, var(I_t)]. This result indicates that the Standardized Anomaly Index is virtually as good, in terms of total variance explained, as the best possible weighted average. In fact, the first principal component applies weights to the 20 rainfall stations that are nearly the same as those for the Standardized Anomaly Index. Since the principal components analysis is based on the correlation matrix for the rainfall data, identical weights (all equal to $1/N$ or 0.05 on a scale normalized to sum to one) would be equivalent to the Standardized Anomaly Index (1). Indeed, all but one of the weights for the first principal component fall between 0.033 and 0.066. In this regard, Richman (1983) has noted that the first principal component commonly behaves like an "average" when applied to anomaly fields of climatological variables. When principal components analysis is applied instead to the covariance matrix, consistent results are obtained; in particular, the weights are roughly proportional to the reciprocal of the standard deviation.

The principal components analysis, unfortunately, implies that any index, consisting of a weighted average, leaves a large portion of the variation in Sahel rainfall "unexplained." This result is indicative of the relatively weak correlations within fields of rainfall data and is consistent with other principal components analyses of precipitation (e.g., Kutzbach, 1967). The question remains as to whether the information about the field of Sahel rainfall data that the Standardized Anomaly Index (or any other simple index) is unable to explain is of any practical significance. Noting that a negative index value is commonly considered as indicative of "below normal" rainfall for a region (e.g., Kerr, 1985), one way to address this issue is by making a comparison of the sign of the index with the signs of the standardized anomalies for the individual stations. Table 2 gives the number of individual stations having below average rainfall year by year, a statistic most meaningfully considered in percentage terms to adjust for missing data. In years for which the Standardized Anomaly Index is

TABLE 2. Comparison of sign of Standardized Anomaly Index with signs of standardized anomalies for individual stations in the Sahel.

Year	Sign of index	Number of stations with below average rainfall*	Year	Sign of index	Number of stations with below average rainfall*
1941	−	12 (17)	1962	+	9 (20)
1942	−	10 (17)	1963	+	9 (20)
1943	+	2 (18)	1964	+	5 (20)
1944	−	10 (17)	1965	+	7 (20)
1945	+	5 (18)	1966	+	10 (20)
1946	+	6 (18)	1967	+	12 (20)
1947	−	12 (18)	1968	−	16 (20)
1948	−	11 (18)	1969	+	10 (20)
1949	−	11 (17)	1970	−	15 (20)
1950	+	2 (20)	1971	−	19 (20)
1951	+	7 (20)	1972	−	19 (20)
1952	+	2 (20)	1973	−	16 (18)
1953	+	5 (20)	1974	−	13 (16)
1954	+	5 (20)	1975	−	10 (20)
1955	+	2 (20)	1976	−	16 (20)
1956	+	10 (20)	1977	−	18 (18)
1957	+	5 (20)	1978	−	12 (20)
1958	+	6 (20)	1979	−	19 (20)
1959	+	9 (20)	1980	−	14 (20)
1960	−	11 (18)	1981	−	19 (20)
1961	−	10 (20)			

* Total number of stations given in parentheses.

below zero, the percentage of individual stations with below average rainfall ranges from 50% (10 out of 20) in 1961 and 1975 to 100% (18 out of 18) in 1977 and averages about 74% (or about 15 out of 20). In years for which the Standardized Anomaly Index is above zero, the percentage of individual stations with below average rainfall ranges from 10% (2 out of 20) in 1950, 1952 and 1955 to 60% (12 out of 20) in 1967 and averages about 32% (or 6 to 7 out of 20). Hence, a substantial fraction of the Sahel sites can have above (below) average rainfall in a year which the index characterizes as below (above) normal.

4. Implications

At first glance, an examination of the properties of a particular rainfall index may appear to have little relevance to assessments of the impact of drought on society in arid and semiarid regions. Yet there is a strong desire to develop indices for all factors in nature and society. Such indices are commonly relied on by decision makers (e.g., those charged with emergency drought relief) to characterize a region's level of precipitation and its concomitant effects on society. If it is properly formulated, if its limitations are recognized, and if it is used with other relevant information such as drought-related population migration, nutritional levels, grain prices in the marketplace and the like, then an index can be very useful. Its misuse and misinterpretation, however, may lead to the development of policies that are inappropriate for combatting environmental and societal effects of droughts. In particular, there should not be an overreliance on any single index to monitor droughts.

Accurate knowledge of the properties of such rainfall indices is also of potential value to those whose decisions rely on the proper use of information on climate. Glantz and Katz (1985), for instance, illustrate certain characteristics of rainfall by producing simulated sequences of a rainfall index by means of a time series model. Such information has become part of the planning debate for dealing with droughts in Africa (e.g., Economic Commission for Africa's Scientific Round Table on the Climatic Situation and Drought in Africa, Addis Ababa, held in 1984).

These properties of rainfall indices might also be useful in conjunction with so-called "teleconnection" studies that attempt to relate rainfall (and especially droughts) in a particular region to atmospheric or oceanic variables far removed from that location (e.g., Quinn et al., 1978; Ramage, 1983). When such cross correlations (i.e., measures of the strength of teleconnections) are calculated, the characteristics of the rainfall index time series are often ignored. This omission means that a linkage between, for instance, El Niño and a rainfall index for a particular region may not necessarily be easily translated into terms that are meaningful for those researchers involved in the assessment of the impacts of droughts or in the development of drought-mitigation strategies.

The application of rainfall indices to the West African Sahel has been emphasized in the present paper. It would be of interest to examine the performance of the Standardized Anomaly Index when applied to rainfall data in other regions, such as the Brazilian Northeast. Preliminary results suggest that, among other things, the rainfall index for the Brazilian Northeast does not exhibit the relatively high degree of autocorrelation characteristic of the Sahel rainfall index.

This paper has concentrated on one particular index of rainfall, the so-called Standardized Anomaly Index. Additional work might involve the consideration of the statistical properties of other forms of indices that are currently used. For instance, an index obtained by ranking the rainfall at an individual station with respect to the station's historical record and then averaging these ranks over all the stations has been employed by Rasmusson and Carpenter (1983). Further, an index based on dividing the rainfall at an individual station by the mean of the station's historical record to obtain a "percent of normal" value and then averaging these percentages over all the stations has sometimes been used (e.g., Winstanley, 1973, 1985). Which of these indices would be superior necessarily depends upon the intended use. Nevertheless, we contend that any of these indices would have limitations analogous to those possessed by the Standardized Anomaly Index.

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REFERENCES

Anderson, T. W., 1958: *An Introduction to Multivariate Statistical Analysis,* Wiley, 374 pp.

Box, G. E. P., and G. M. Jenkins, 1976: *Time Series Analysis: Forecasting and Control,* rev. ed. Holden-Day, 575 pp.

Glantz, M. H., and R. W. Katz, 1985: Drought as a constraint to development in sub-Saharan Africa. *Ambio* (in press).

Granger, C. W. J., and P. Newbold, 1977: *Forecasting Economic Time Series,* Academic Press, 333 pp.

Hastenrath, S., 1984: Predictability of north-east Brazil droughts. *Nature,* **307,** 531–533.

——, M.-C. Wu and P.-S. Chu, 1984: Towards the monitoring and prediction of north-east Brazil droughts. *Quart. J. Roy. Meteor. Soc.,* **110,** 411–425.

Hogg, R. V., and A. T. Craig, 1970: *Introduction to Mathematical Statistics,* Macmillan, 415 pp.

Katz, R. W., 1978: Persistence of subtropical African droughts. *Mon. Wea. Rev.,* **106,** 1017–1021.

——, 1985: Properties of cross correlation functions: Implications for teleconnections research. *Preprints, Ninth Conf. on Probability and Statistics in Atmospheric Sciences,* Virginia Beach, Amer. Meteor. Soc., 271–275.

——, and M. H. Glantz, 1977: Rainfall statistics, droughts and desertification in the Sahel, *Desertification: Environmental Degradation in and Around Arid Lands,* M. H. Glantz, Ed., Westview, 81–102.

Kerr, R. A., 1985: Fifteen years of African drought. *Science,* **227,** 1453–1454.

Kraus, E. B., 1977: Subtropical droughts and cross-equatorial energy transports. *Mon. Wea. Rev.,* **105,** 1009–1018.

Kutzbach, J. E., 1967: Empirical eigenvectors of sea-level pressure, surface temperature and precipitation complexes over North America. *J. Appl. Meteor.,* **6,** 791–802.

Lamb, P. J., 1982: Persistence of Subsaharan drought. *Nature,* **299,** 46–48.

——, 1983: Subsaharan rainfall update for 1982: continued drought. *J. Climatol.,* **3,** 419–422.

Lindgren, B. W., 1968: *Statistical Theory,* 2nd ed., Macmillan, 521 pp.

Mayer, J., 1985: Preventing famine. *Science,* **227,** 707.

Nicholson, S. E., 1983: Sub-Saharan rainfall in the years 1976–80: evidence of continued drought. *Mon. Wea. Rev.,* **111,** 1646–1654.

Quinn, W. H., D. O. Zopf, K. S. Short and R. T. W. Kuo Yang, 1978: Historical trends and statistics of the Southern Oscillation, El Niño, and Indonesian drought. *Fish. Bull.,* **76,** 663–678.

Ramage, C. S., 1983: Teleconnections and the siege of time. *J. Climatol.,* **3,** 223–231.

Rasmusson, E. M., and T. H. Carpenter, 1983: The relationship between eastern equatorial Pacific sea surface temperature and rainfall over India and Sri Lanka. *Mon. Wea. Rev.,* **111,** 517–528.

Richman, M. B., 1983: Rotation of principal components in climatological research. Part I: Theoretical considerations, suitable applications and advantages over unrotated solutions. *Preprints, Eighth Conf. on Probability and Statistics in Atmospheric Sciences,* Hot Springs, Amer. Meteor. Soc., 59–68.

Wigley, T. M. L., K. R. Briffa and P. D. Jones, 1984: On the average value of correlated time series, with applications in dendroclimatology and hydrometeorology. *J. Climate Appl. Meteor.,* **23,** 201–213.

Winstanley, D., 1973: Recent rainfall trends in Africa, the Middle East and India. *Nature,* **243,** 464–465.

——, 1985: Africa in drought: A change of climate? *Weatherwise,* **38,** 74–81.