Meteorological Drought Quantification with Standardized Precipitation Anomaly Index for the Regions with Strongly Seasonal and Periodic Precipitation

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Meteorological Drought Quantification with Standardized Precipitation Anomaly Index for the Regions with Strongly Seasonal and Periodic Precipitation

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Abstract: In this study, an index, named as standardized precipitation anomaly index (SPAI), is proposed for the meteorological drought quantification in the context of the monsoon-dominated climatology, where the precipitation is strongly seasonal and periodic. In the computation of SPAI, the anomalies of the precipitation are normalized rather than normalizing the raw precipitation series. The SPAI is compared with the standardized precipitation index (SPI), with respect to certain shortcomings of the latter. It is shown that the SPAI, owing to its design, is able to successfully differentiate between the consequences of shortages/surplus in rainfall in the monsoon and nonmonsoon months which is not possible through SPI. The unique suitability of SPAI for monsoon dominated regions is also illustrated by comparing its premise of development with that of the standardized nonstationary precipitation index (SnsPI). Further, drought quantification through the SPAI is shown to be applicable for both periodic and nonperiodic precipitation series. This is demonstrated using a typical strongly periodic precipitation series (from India) and a typical nonperiodic precipitation series (from Arkansas, United States of America). As compared with SPI, the SPAI is found to have a better coherence with the consequences of droughts and wet spells faced by the country (India, as the study area) in the past. **DOI: 10.1061/(ASCE)HE.1943-5584.0001236.** *© 2015 American Society of Civil Engineers.*

Author keywords: Meteorological drought; Standardized precipitation anomaly index (SPAI); Standardized precipitation index (SPI); Standardized nonstationary precipitation index (SnsPI); Seasonality; Periodicity; Precipitation.

Introduction

Because precipitation is the primary input to the watershed system, insufficient precipitation is the cause of all forms of drought (Dracup et al. 1980; Wilhite and Glantz 1985; Heim 2002). Standardized precipitation index (SPI) (McKee et al. 1993, 1995) is one of the most popular meteorological drought indices and is in use all across the world. Since its inception, various modifications have been introduced in the SPI methodology by several researchers to address numerous issues (Guttman 1999; Vincente-Serrano 2006; Dubrovsky et al. 2009; Türkeş and Tatli 2009; López-Moreno et al. 2009; McRoberts and Nielsen-Gammon 2011; Pietzsch and Bissolli 2011; Russo et al. 2013). The current version of SPI, where the parameters of the monthwise probability distribution models are determined separately, has been studied and used widely by researchers over a diverse range of climates (Ntale and Gan 2003; Rouault and Richard 2003; Mihajlović 2006; Wu et al. 2007; Husak et al. 2007; Dubrovsky et al. 2009; Mishra and Desai 2005; Bothe et al. 2010; Vicente-Serrano et al. 2010, 2012). The SPI is generally appealing because it is able to standardize precipitation that can be compared across time and space. However, there are certain aspects of the SPI that limits its ubiquitous use. For instance, Wu et al. (2007) showed that in arid climates or dry seasons, where the frequency of zero values (no precipitation cases) is high, the SPI values are lower bounded and fail to adequately indicate a drought occurrence. Another limitation of SPI is its unsuitability for a long data series whose nature changes significantly during the time of study. To incorporate the variability of a long precipitation data series, a modification of the SPI was suggested by Russo et al. (2013) and consequently the standardized nonstationary precipitation index (SnsPI) was developed. In general, the SPI has certain shortcomings. First, even a small deficit in precipitation may be reflected as a large negative SPI value for the locations with small variation in precipitation (Lloyd-Hughes and Saunders 2002; Mallya et al. 2013). Second, the same holds true for seasons with small variation in precipitation. A small precipitation deficit (surplus) in a season with low precipitation variation and a large precipitation deficit (surplus) in a season with high precipitation variation may each be reflected as large negative (positive) SPI values. Such dry (wet) events may be statistically similar, but they need not always translate to similar social consequences in community life; the climatology of the study area plays a pivotal role. A typical example would be the monsoon dominated regions, which receive most of the rainfall during some particular months in a year. For instance, India receives approximately 78% of the total annual rainfall during the four monsoon months of June through September (JJAS) (Mooley and Parthasarathy 1984). The rainfall during this period is crucial because the economic growth of the country heavily depends on it. Moreover, this is the time when depleted surface-water sources are replenished for use during the rest of the year. As a result, a deficit in monsoon rainfall would have huge repercussions on the agricultural sector which accounts for approximately 51% of the total employment in India according to data released by the World Bank in 2010 (available from http://data.worldbank.org/indicator/SL.AGR.EMPL.ZS), contributing approximately 13% of the total GDP [Ministry of Statistics and Programme Implementation (MOSPI) 2012]. On the

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other hand, the rainfall deficit in the winter or summer (November to May) has little socioeconomic implications in India because scanty rainfall is generally expected in these seasons, and water requirement is generally met from other sources. Hence, when an assessment of drought is required from the social repercussion point of view, the SPI (owing to its design) may not reflect the social consequences caused by deficit/surplus rainfall across both the high and low rainfall month(s). For example, a rainfall deficit of 8.74 mm in January (traditionally dry month) and 68.73 mm in August (monsoon month) result in more or less similar values of SPI (say −2, detailed calculations are provided later). However, the consequences attributable to the rainfall deficit corresponding to a SPI value of −2 in a traditionally dry period (nonmonsoon months) is very different from the same corresponding to the similar SPI value in a climatologically wet period (monsoon months). The two events may be statistically equally frequent (or infrequent), but have vastly contrasting socioeconomic impacts. Such issues may lead to practical difficulties while planning drought response activities. This presents the background for the development of an appropriate index which can address the aforementioned challenges. The anomaly based index proposed in this study may be able to differentiate between the aforementioned rainfall deficits (8.74 mm in January and 68.73 mm in August), which constitutes the motivation behind the development of the new index.

Considering the aforementioned issues, the community or administration may need an index that simultaneously considers high rainfall (e.g., monsoon) and low rainfall (e.g., nonmonsoon) periods, and successfully differentiates the consequences attributable to shortages/surplus of rainfall magnitude in both monsoon and nonmonsoon month(s) without putting any subjective justification. Thus, the objective of this study is to quantify meteorological drought through a proposed index, named as, standardized precipitation anomaly index (SPAI). First, the benefits of SPAI is explored in the context of the regions with (monsoon-dominated) strongly seasonal precipitation, where life revolves around rainfall dependent activities, such as, agriculture, for a majority of the population. The contrasting features between the SPI and the proposed SPAI are demonstrated in such situations. A comparison of the relative suitability of SPAI with SnsPI, which was developed earlier (Russo et al. 2013) to take care of a few shortcomings of SPI, is presented. This comparison reveals the utility of the proposed index over the existing SnsPI in the context of monsoon dominated strongly periodic precipitation regimes. Further, it is demonstrated that the SPAI, being a more generalized index, converges with the SPI in absence of the seasonality in precipitation, indicating the suitability of the former for nonperiodic precipitation as well.

Study Area and Data

Monthly precipitation data over entire India (aka *all India*) and from two meteorological subdivisions of India [Gangetic West Bengal (GWB) and Orissa] are obtained from India meteorological department (IMD), Pune for the period 1951–2010. The data are obtained from the Indian Institute of Tropical Meteorology (IITM) (available at www.tropmet.res.in). For development of the data, a network of 306 rain gauge stations over 30 meteorological subdivisions of India are considered which cover an area of approximately 2,880,000 km^2, which is approximately 90% of the total area of India (ftp://www.tropmet.res.in/pub/data/rain/iitm-imr-readme.txt). Daily precipitation data of the Saint Charles station (SCS) (GHCND: USC00036376), Arkansas, United States of America is also obtained from NCDC, NOAA, United States of America and the monthly precipitation values, required for this study, are derived from it. A spectral analysis (Haan 1977) (using rainfall data from 1951 to 2000) indicates that monthly rainfall data from both GWB and Orissa exhibit strong periodicity (Fig. 1) of 12 months (annual cycle) and six months (biannual cycle). This is typical for Indian rainfall. However, the rainfall from SCS does not indicate any periodicity. Hence, the rainfall series from GWB and all India are used as the examples of periodic rainfall series, whereas that from SCS is used as an example of nonperiodic rainfall series.

Methodology

Computation of Standardized Precipitation Index

As per McKee et al. (1993, 1995), the SPI is computed from an observed precipitation time series (at least 30–40 years) by fitting a gamma distribution to the raw precipitation data. The cumulative distribution function (CDF) of the gamma distribution is then transformed to standard normal variate (Z) to obtain SPI. SPI may be computed for various temporal scales ranging from one-month to 36-month or even 48-month intervals (Edwards and McKee 1997) to describe drought conditions for a range of meteorological, agricultural, and hydrological applications. For one-month SPI, precipitation is normalized for each month of the year (McKee et al. 1993, 1995; Wu et al. 2005). Because precipitation series may include some zero rainfall values, each of the 12 monthly rainfall series are modeled by a mixed probability distribution given by (Edwards and McKee 1997)

$$H(x) = \begin{cases} q & x = 0 \\ q + (1-q)G(x) & x > 0 \end{cases} \tag{1}$$

where $q = m/N$, (m being the number of months with no rainfall in a series and N being the total number of months in the series) is the probability of zero rainfall, and $G(x)$ is the cumulative gamma distribution fitted to the nonzero rainfall data, (x), and $H(x)$ is the CDF of the mixed probability distribution of rainfall

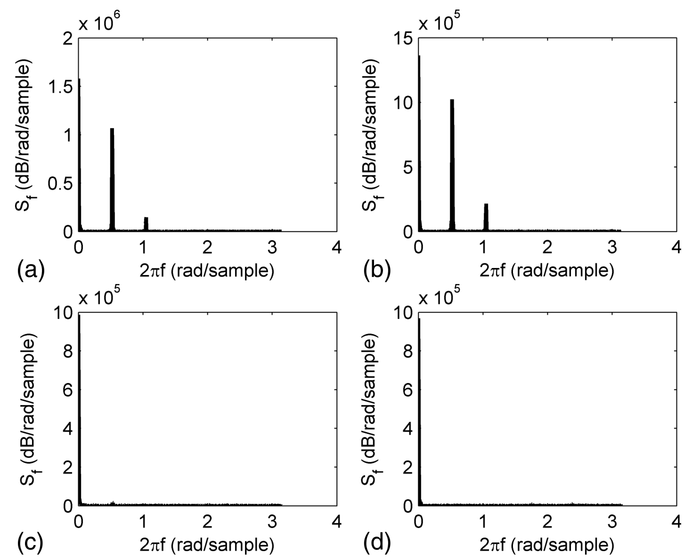

Fig. 1. Periodograms of 50 years monthly precipitation data for: (a) GWB, India; (b) Orissa, India; (c) SCS, U.S.; (d) generated random series (600 data points) having gamma distribution with parameters 2.11 and 48.82: strong seasonality is evident in (a) and (b) plots

series for the concerned month. The CDF of gamma distribution is given by

$$G(x) = \int_0^x \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} dx \qquad x \geq 0 \quad \text{and} \quad \alpha, \beta > 0 \tag{2}$$

where α and β, are the shape and scale parameters, respectively. For each of the 12 monthly rainfall series, $H(x)$ is transformed to standard normal variates (Z) to obtain the month-wise SPI series, which are then reorganized into a chronological series.

Standardized Nonstationary Precipitation Index (SnsPI)

It is worthwhile to present here a brief explanation of the methodology of computation of the SnsPI, as it was developed to incorporate the variability of long precipitation datasets which cannot be appropriately handled by the SPI. The SnsPI is obtained by fitting the precipitation data to a nonstationary gamma distribution with a fixed shape parameter but a time varying scale parameter. This is implemented by expressing the mean of the rainfall series in terms of a time-dependent linear equation. The SnsPI may be computed at various temporal scales. Because we have a considered monthly scale in the case of the SPI and SPAI, the same may be considered here as well. Hence, if X_t represents the monthly rainfall series for any particular month, say January, and μ_t represents the nonstationary mean rainfall for that month, then

$$E(X_t) = \mu_t = b_1 + b_2 t \tag{3}$$

where b_1 and b_2 = constants; and t = time step. Thus, the mean rainfall for the month of January is not a constant, rather it is a function of time. The next step is to express this nonstationary monthly rainfall series as a gamma distribution, which is also used in the case of SPI. Thus, $X_t \sim \text{Gamma}\,(\alpha, \beta_t)$, where α and β_t are the shape and scale parameters, respectively. The scale parameter β_t may be expressed as

$$\beta_t = \frac{\mu_t}{\alpha} \tag{4}$$

If there are zero rainfall values at the monthly scale, then a mixed distribution, consisting of a concentrated probability and a gamma distribution, may be considered, as as explained in the case of SPI. Subsequently, for each of the 12 monthly rainfall series, the cumulative distribution is transformed to standard normal variates (Z) to obtain the month-wise SnsPI series, which are then reorganized into a chronological series.

Computation of Standardized Precipitation Anomaly Index

In the computation of SPAI, the precipitation anomalies are used instead of raw precipitation values. The anomalies of precipitation are given by

$$y_{i,j} = (x_{i,j} - \bar{x}_j) \tag{5}$$

where $y_{i,j}$ = precipitation anomaly for the ith year and jth time step of the year; $x_{i,j}$ = precipitation value for the ith year and jth time step of the year; $\bar{x}_j$ = long-term mean precipitation for the jth time step of the year. Noteworthy is that the unit of the rainfall anomaly series is the same as that of the rainfall series. This needs to be standardized to convert to the scale of Z score. It is explained as follows.

After obtaining the anomalies, a single probability distribution is fitted to the entire anomaly series (y). Gaussian distribution, t-location-scale distribution, three-parameter gamma (aka Pearson type-III distribution) or empirical distribution are various options to model the anomaly series. It is noted that because anomalies are not lower bounded by zero, the gamma distribution (commonly used in SPI computation) is not applicable here. Though Gaussian distribution might be most preferable among the alternatives, considering the higher order moments of rainfall anomaly series, it may not pass the statistical test(s) of distribution fitting. If a sufficiently long dataset (>30–35 years) is available, an empirical distribution would be a good choice.

Whereas goodness-of-fit tests are mandatory for parametric distributions, such as t-location-scale distribution and three-parameter gamma distribution, the empirical distribution estimates the true underlying CDF of the points in the sample. To obtain the empirical CDF of the rainfail anomaly series (y), the Weibull's plotting position formula is found to be the best for plotting position (Makkonen 2006) and is expressed by

$$p = \frac{m}{N+1} \tag{6}$$

where p = cumulative probability; m = rank of the dataset arranged in descending order; and N = sample size as explained before, i.e., the total number of time steps in the dataset.

After fitting the empirical distribution, the quantile values corresponding to each anomaly values are obtained. These quantile values, ranging from 0 to 1, may be designated as the *reduced variates* of the rainfall anomalies. Next, these reduced variates are transformed to standard normal variates (Z), i.e., the numbers on the real line which would correspond to the values of reduced variates in a standard normal distribution are determined. The obtained standard normal variates (Z) are the required SPAI. Similar to the SPI, SPAI values also range between $-\infty$ and $+\infty$ where negative (positive) values reflect drier (wetter) conditions.

The SPAI may be computed at any temporal scale, such as, one-month (SPAI-1), three-month (SPAI-3), and six-month (SPAI-6) periods. Considering that SPAI-3 is being computed, first, the series of precipitation totals at the time scale of interest (three months) is obtained. The anomalies are then computed by subtracting the mean precipitation during the concerned time period. Thus, the precipitation totals over January-February-March, February-March-April, for example, form the series of precipitation totals [x in Eq. (5)]. The long-term mean precipitation over January-February-March and February-March-April [$\bar{x}$ in Eq. (5)] must be correspondingly subtracted to obtain the three-month precipitation anomaly series (y) as per Eq. (5) by designating j as the corresponding time step. Next, Eq. (6) is applied to the entire anomaly series to obtain the cumulative probability (reduced variates) corresponding to each three-month precipitation anomaly value. The reduced variates are then transformed to standard normal variates (Z), which gives the SPAI series. In this particular study, the researchers have used one month as the temporal scale. Hence, the monthly rainfall datasets and monthly anomalies were used.

As outlined above, the two major methodological differences introduced in SPAI with respect to SPI are (1) the precipitation anomalies are used instead of raw precipitation values, and (2) a single probability distribution is fitted across the monthly anomaly series, instead of 12 different distributions used in SPI. It is noted here that both the methodological differences introduced in this index contribute to fulfilling the objective of this study, i.e., devising a suitable index for correct indication of dry and wet extremes of a periodic precipitation series, where the mean rainfall is very different in various months of the year. If a single probability distribution is directly fitted to the rainfall values (rather than the anomalies), then the low-rainfall months (nonmonsoon months) would always appear as dry extreme and high-rainfall months (monsoon months) would always appear as a wet extreme in the final series of the index. In that case, the index values would be hardly of any use because they cannot pick up unusually dry monsoon months which affect agriculture and have far-reaching socioeconomic implications. Thus, the rainfall anomalies are used to assess how low/high the rainfall is when compared with the long-term average for that time of the year.

Regarding the second methodological difference, if the monthly rainfall anomalies are fitted to 12 different distributions (rather than a single distribution), then similar extreme index values (say, a value of −2) may result during a nonmonsoon month and a monsoon month. In reality, these may correspond to very different socioeconomic conditions, because the mean rainfall during such months is very much different from each other. The merits of the methodological basis of constructing the SPAI will be clearly revealed in the "Results and Discussion" section which provide comparisons of the SPAI and SPI.

Results and Discussion

At one-month temporal scale, the series of the SPAI and SPI for GWB, all-India and SCS rainfall are obtained. For the SPAI, the empirical distribution, explained earlier, has been used because a reasonably long data set is available. The data during 1951–2000 are considered as the base period for computing the long-term mean in both the cases. Finally, the series of the SPAI and SPI are obtained for the entire study period (1951–2010). The next two sections provide comparisons of the SPAI and SPI with respect to the behavior of the indices in various months in a monsoon-dominated climatology.

Behavior of the SPI in the Context of Precipitation Series with Strong Seasonality

This section presents the behavior of SPI series when applied to a periodic precipitation series. The SPI series (1951–2010) for GWB are plotted for a typical nonmonsoon month (January) [Fig. 2(a)] and a typical monsoon month (July) [Fig. 3(a)] for discussion. To facilitate the discussion, the SPI values for another monsoon month—September is also shown [Fig. 4(a)]. Similarly, for all-India rainfall, the SPI values for January and August are shown in Figs. 5(a) and 6(a), respectively. It is observed that the range of SPI is almost the same for both monsoon and nonmonsoon months.

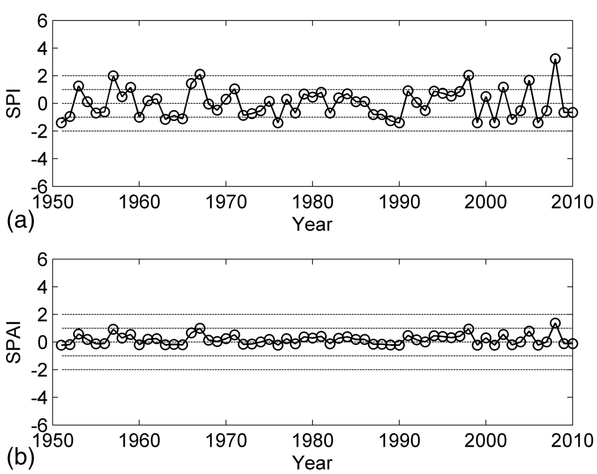

Fig. 2. Series of January: (a) SPI; (b) SPAI values for GWB for the period 1951–2010

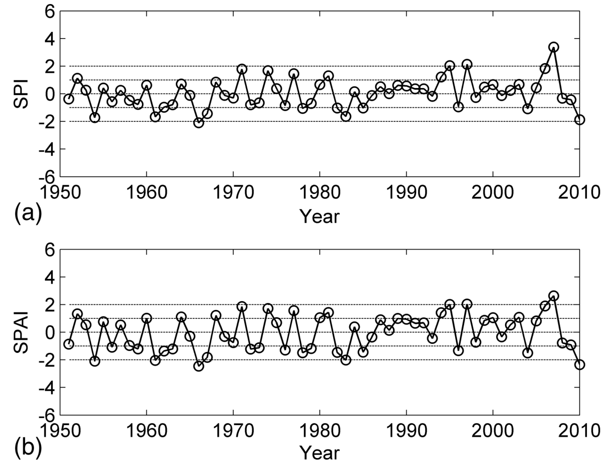

Fig. 3. Series of July: (a) SPI; (b) SPAI values for GWB for the period 1951–2010

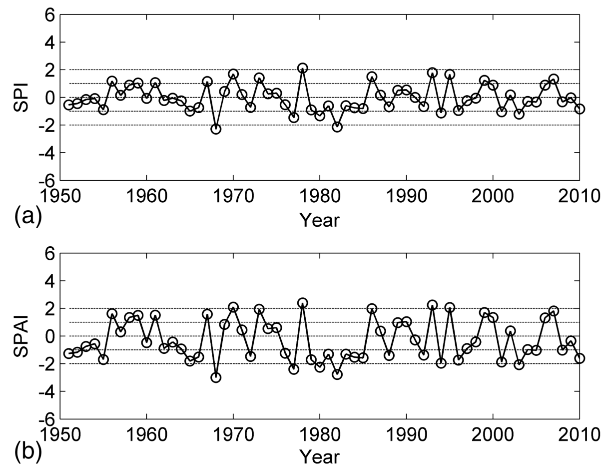

Fig. 4. Series of September: (a) SPI; (b) SPAI values for GWB for the period 1951–2010

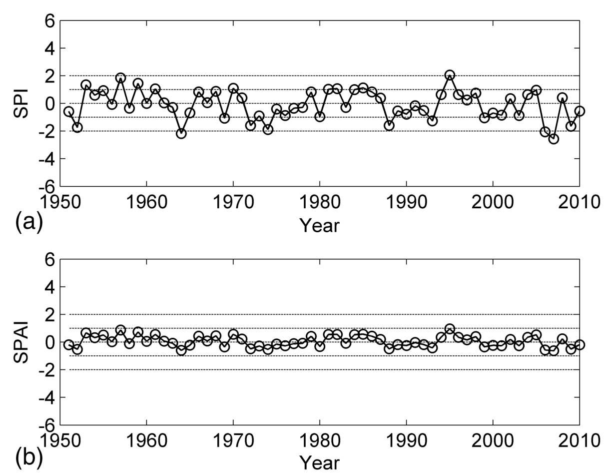

Fig. 5. Series of January: (a) SPI; (b) SPAI values for all India for the period 1951–2010

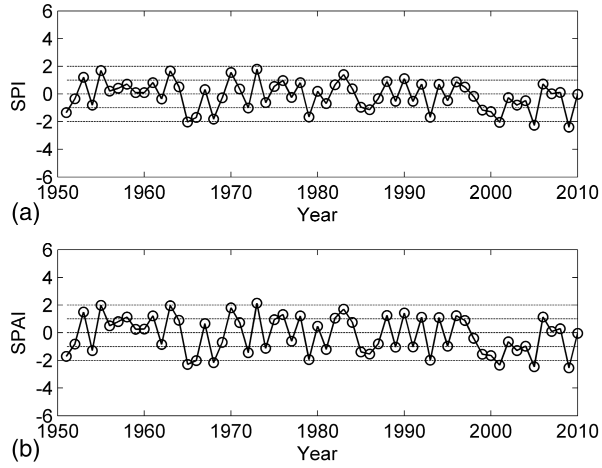

Fig. 6. Series of August: (a) SPI; (b) SPAI values for all India for the period 1951–2010

Similar observations were made for other monsoon and nonmonsoon months also (figures not shown). However, as mentioned before, a given SPI value, when observed in different months (seasons), may have different socioeconomic implications. For instance, in the year 1972, SPI values for the GWB in January and July are quite close to each other, −0.85 and −0.79, respectively. The deficit in rainfall compared with the mean conditions for the respective months are 10.85 and 66 mm, respectively. A deficit of 10.85 mm in January (traditionally a dry month) can have very little socioeconomic impact and may even go unnoticed. On the other hand, a deficit of 66 mm in July (peak monsoon month) may be a cause of serious concern. Thus, the two similar SPI values from different months (season) cannot be compared directly. This demands the prior knowledge of local climate within which policy makers need to take drought-driven decisions. Moreover, it is also noticed that the SPI values in January fall to −1 or below 10 times within the study period, and it attains a value of +1 or above nine times within the study period. However, from the point of view of social consequences, extreme dry or wet events are almost never observed in January in the study area. This is because January has a low mean precipitation (12.16 mm), and a deficit or surplus precipitation during this time of the year does not hamper agricultural or socioeconomic activities. Even if there is no rainfall in January (1951, 1976, 1990, 1999), there is not much cause for concern from the social perspective. However, these events are reflected as extreme events (SPI = −1.405) because these events correspond to the maximum possible deficit in January.

Similar examples are also found in the case of SPI series for all-India [Figs 5(a) and 6(a)]. The SPI values of January 1964 and August 2009 are −2.17 and −2.40, respectively. Both fall in the D4 i.e., *exceptional drought* category. However, in 1964, no drought related consequences are reported, although the year 2009 experienced a major drought which hampered agricultural production, and a remarkable increase of farmer suicide cases in India was reported. At least 17,368 Indian farmers committed suicide in 2009 according to data of the National Crime Records Bureau [National Crime Records Bureau (NCRB) 2009].

Examples are also noticed for other side of extreme, i.e., wet. For GWB, the SPI estimate for January 1967 and September 1978 are 2.10 and 2.12, respectively. Both these values indicate *extremely wet* condition, but the former was hardly a cause for concern, and the latter was potentially dangerous. From the societal point of view, the former went unnoticed by the community, whereas the latter marked one of the rainiest years in the state leading to one of the deadliest floods in recorded history in which at least 1,370 people lost their lives, and approximately 16 million people were affected as per the data provided by the State Inter Agency Group (IAG), West Bengal [a group working with assistance from the Disaster Management Department, Government of West Bengal and United Nations International Children's Emergency Fund (UNICEF)] (IAG 2013). Other similar examples may also be observed during the study period. Thus, a comparison between similar SPI values in different months (seasons) can point out spectacularly dissimilar societal repercussion in a monsoon dominated region.

Potential of the Proposed SPAI in Monsoon-Dominated Climatology

The disadvantages of using the SPI for a monsoon dominated climatology have been illustrated through specific examples in the previous section. This section presents an explanation of how the SPAI can overcome these challenges. Figs. 2(b), 3(b), and 4(b) shows separate plots of SPAI series for January, July, and September, for the period 1951–2010 for GWB. The SPAI series for all India rainfall are shown in Figs. 5(b) (January) and 6(b) (August), respectively. It is evident that the range of SPAI variation is much lower for nonmonsoon months than that for monsoon months. Thus, the SPAI dampens the high fluctuations of its magnitude during nonmonsoon months and reflects a better coherence with the scourges of droughts and extreme wet events actually faced by the community. Hence, SPAI estimates in January mostly show *near normal conditions* [vary between −1 and +1 in Fig. 2(b)]. Let us again consider the year 1972, when the deficit in January rainfall in GWB is 10.85 mm. Though it is significantly (89%) below the January mean of 12.16 mm, it bears no potential danger to the community. The SPAI value was obtained to be −0.15 for this situation as opposed to a SPI value of −0.85 for the same situation. Again, in July 1972, GWB rainfall is 263 mm which is 66 mm below July mean (329 mm) and is cause for concern for the agricultural sector. The SPAI was found to be −1.21, and the corresponding SPI value is −0.79. Thus, the SPAI could differentiate between January 1972 versus July 1972 (−0.15 versus −1.21), whereas the SPI values (−0.85 versus −0.79) do not reflect this difference. Similarly, July rainfall of GWB in 1983 was 120.2 mm (36.5%) below the July mean and was potentially harmful from the socioeconomic point of view. The SPAI value (−2.01) for July 1983 emphasizes this drought situation. Though a negative SPI value (−1.63) is obtained in this month, similar SPI values (−1.41) are also obtained in January 1951 and 1990) also when the rainfall is zero. However, the situation is far from threatening, which is reflected in the SPAI value of −0.22 in these months. To corroborate these findings, let us go back to the example (mentioned in the previous subsection) of January 1964 and August 2009. In both the cases, all-India SPI values indicate D4 i.e., exceptional drought category. However, SPAI estimate for the former is −0.6, which is in agreement with the fact that no drought related loss is reported in that year. However, in August 2009, the SPAI value is −2.54 which is indicative of the major drought experienced in that year, when documented records indicate heavy losses in the agricultural sector and a remarkable increase of farmer suicide (as mentioned before).

On the other side of the extreme (i.e., wet), let us consider the previous example of January 1967 (and also January 1957 and 1998) and September 1978. In each of these cases, SPI for GWB indicate *extremely wet* situation. However, the SPAI estimate for January, 1967 is 1.0 (0.93 for January 1957 and 0.94 for January 1998), whereas it is 2.40 for September 1978. This effectively reflects the ground reality—the societal impacts of the former are innocuous, whereas that of the latter is devastating (administrative records are reported earlier). Thus, unlike SPI, SPAI can distinguish between (statistically) similar deficits across different months (periods), which have contrasting socioeconomic implications in a monsoon-dominated climatology. This issue is of utmost importance for better planning of drought response activities and mitigation strategies.

SPAI versus SnsPI

This section explores the applicability of SnsPI for periodic precipitation series observed in monsoon dominated climatology. The SnsPI is designed to incorporate the variability of long precipitation datasets. However, for the study area, it is found that there is no significant trend either in the mean monthly rainfall series for a given month of the year or for the chronological monthly time series during the study period. Fig. 7 shows the variation of the mean monthly rainfall over India during the study period (1951–2010). It is expressed in the form of a time variant linear equation [as per Eq. (3)], as follows:

$$\mu_t = 91.006 - 0.003 \times t \tag{7}$$

The slope is found to be very small (insignificant with p-value $= 0.87$). In the absence of any trend, the SnsPI is expected to be no different from SPI. To investigate this, the linear variation of mean rainfall was obtained, and the SnsPI was computed following the method explained earlier.

For each month of the year, the time variation of mean rainfall was expressed in the form of Eq. (3). The computed month-wise SnsPI series was arranged chronologically to obtain the final SnsPI series. A comparison [Figs. 8(a and b)] of the SPI and SnsPI for the months January and July indicates that the inadequacies in SPI for handling strongly periodic rainfall series are present in SnsPI also, thus making both of them unsuitable for the present context of monsoon dominated climatology. Thus, it is concluded that the SnsPI might be suitable for rainfall series with distinct observable trend and useful for modeling the change in precipitation trend attributable to climate change. However, during the study period, the Indian rainfall series does not have any noticeable trend, rather a strong seasonality is evident which is best handled by the SPAI, which is adequately designed for this purpose as explained in details earlier in this paper.

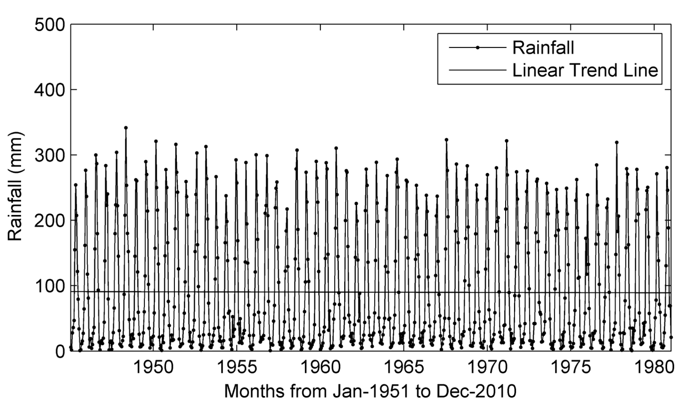

Fig. 7. All India monthly rainfall time series from January 1951 to December 2010

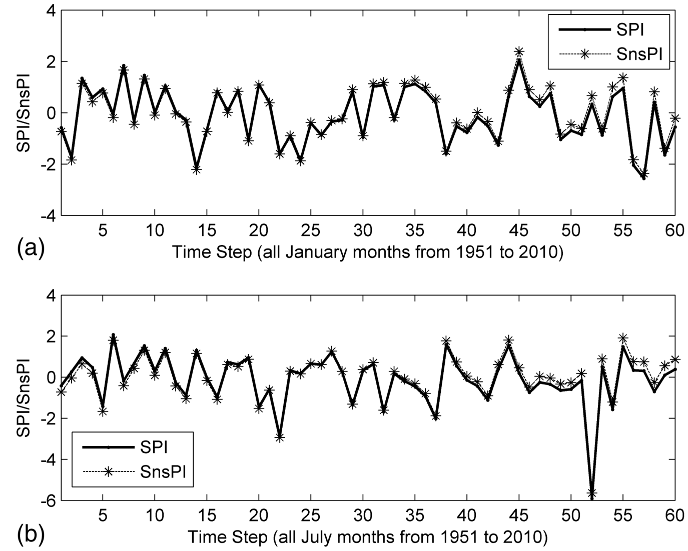

Fig. 8. Series of SPI and SnsPI for all India rainfall during 1951–2010 for the month of (a) January; (b) July

Applicability of the SPAI for Nonperiodic Rainfall Series

Having established the relative merits of SPAI over SPI (and SnsPI) for a periodic precipitation series through the previous sections, this section explores the applicability of SPAI for a nonperiodic precipitation series. Using spectral analysis, it was shown previously that the rainfall data from SCS does not indicate any periodicity (Fig. 1). Fig. 9 shows the plots of SPI and SPAI for January for the nonperiodic rainfall series of SCS for the period 1951–2000. Similar plots for the month of July are shown in Fig. 10. It is interestingly observed that unlike in the case of the periodic precipitation dataset for GWB, India, where the correlation coefficient between the proposed SPAI and SPI is 0.90 [Fig. 11(a)], the two indices provide similar results in the case of SCS, the correlation coefficient being 0.98 [Fig. 11(b)]. This issue is further explored by simulating a random series (to ensure complete absence of periodicity) having gamma distribution with shape parameter 2.11 and scale parameter 48.82 (same as the parameters of the nonperiodic precipitation series from SCS).

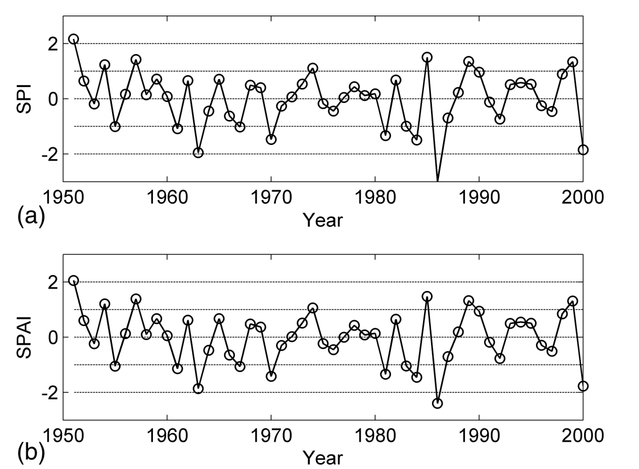

Fig. 9. Series of January: (a) SPI; (b) SPAI values for SCS for the period 1951–2000

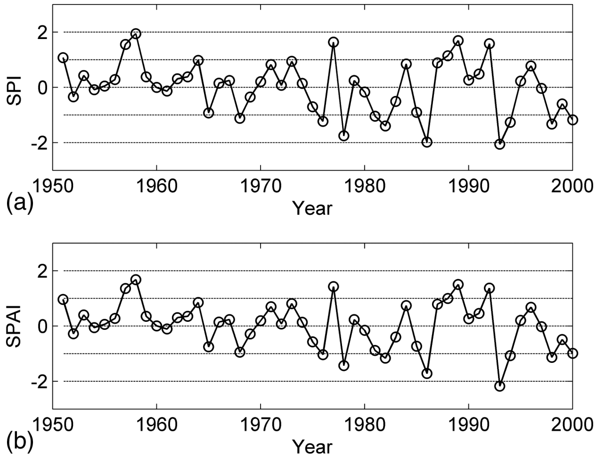

Fig. 10. Series of July: (a) SPI; (b) SPAI values for SCS for the period 1951–2000

The SPI and SPAI are computed for this simulated series, and the correlation is found to be very high (0.99) [Fig. 11(c)]. In Fig. 11(a), it is further noticed that there are 12 trails of scatter of different slopes which correspond to the 12 months. Thus, for each of the 12 months, the ratio of SPAI and SPI are clearly different. This indicates that the values of SPAI for the dry months are so oriented that they form lines of smaller slope, because these values fluctuate within a smaller range. On the other hand, the lines created from the SPAI values of monsoon months make a steeper slope as the range of SPAI values are larger for such months. Fig. 11(b) corresponds to the nonperiodic precipitation series of SCS, and the correlation between the two indices should ideally be 1 here. Practically, it comes as 0.98. In Fig. 11(c), the scatter plot between the two indices is shown for an artificially created gamma distributed series. Here also, the correlation should be ideally 1, which is practically obtained as 0.99 here. This indicates that the SPAI and SPI provide essentially the same values when the rainfall dataset is nonperiodic. However, they differ for the seasonally periodic rainfall and in such cases, the SPAI values are found to be in agreement with the possible socioeconomic implications on the community. Thus, SPAI can be used for both periodic and nonperiodic rainfall series, whereas the SPI, because of its design, does not reflect the societal repercussion of extreme events across high and low rainfall months (periods).

It is worthwhile to note that in the present illustration an empirical probability distribution has been used for constructing the SPAI. In situations where a sufficiently long dataset is not available, parametric probability distributions such as *t*-location scale distribution or three-parameter gamma distribution should be used. Another noteworthy point is that, like SPI, SPAI also suffers from the limitation that it is not very meaningful for large temporal scales such as 12 months or more. At such scales, the accumulated precipitation totals have too much temporal overlap and are no longer independent. The interannual variability of the dry and wet conditions would be missed at such scales. So SPAI should be ideally applied for smaller (<12 months) temporal scales.

Conclusions

This study proposes an anomaly based index, i.e., SPAI, for meteorological drought quantification and explores its potential in distinguishing between (statistically) similar interseasonal deficits which have contrasting socioeconomic implications in a monsoon-dominated climatology. The proposed SPAI, owing to its design, is able to distinguish between actual consequences of dry events occurring in monsoon (high rainfall) and nonmonsoon (low rainfall) months. This makes it readily usable considering the practical perspectives in monsoon and nonmonsoon seasons. In case of the widely used SPI, a very low value may or may not be cause for drought concern, depending on the month/season it refers to. Thus, the interpretation of the SPI values might be difficult without the knowledge of climatology of the study area, and one needs to subjectively decide whether an extreme SPI value requires attention or not in a certain month/season for drought monitoring purpose. This is addressed in SPAI which reports insignificant values if the deficit/surplus is irrelevant based on the long-term climatology of the study area. SPAI, by design, dampens the high fluctuations of the index in nonmonsoon months and reflects a better coherence with the scourges of high and low rainfall events, actually faced by the community. The study also shows that the SnsPI, which was developed as an improvement to SPI, to incorporate the nonstationarity of long precipitation datasets, is not suitable for the monsoon-dominated periodic precipitation series wherein the SPAI is established to be ideally suited. While investigating the applicability of SPAI for nonperiodic rainfall series, the SPAI and SPI are found to essentially converge for nonperiodic rainfall series. However, that is not the case for periodic rainfall series. Thus, the SPAI is a more general index and shows promise for meteorological drought quantification that can be utilized for monsoon dominated regions having a strongly periodic precipitation pattern.

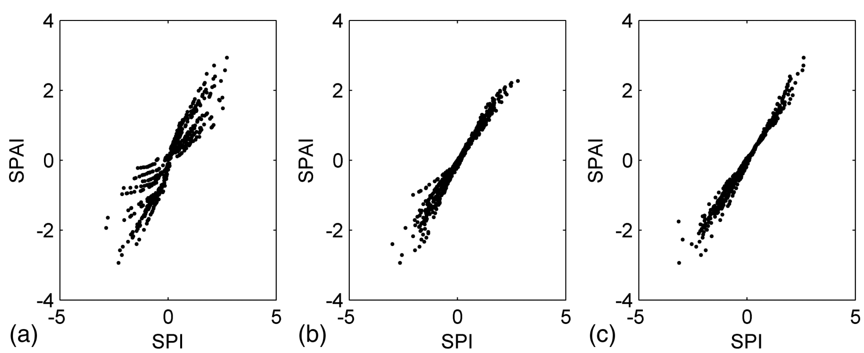

Fig. 11. Comparison of 1-month SPI and 1-month SPAI series for: (a) strongly periodic precipitation series (GWB, India) (correlation coefficient $r = 0.90$); (b) nonperiodic precipitation series (SCS) ($r = 0.98$); (c) simulated random series having gamma distribution with parameters 2.11 and 48.82 ($r = 0.99$): SPI and SPAI are practically the same if the precipitation series is nonperiodic

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