Using the Standardised Precipitation Index (SPI) for short-term drought: a review

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Abstract

This paper compares the binomial distribution (BD), the plotting position (PP), and the original method (OM) to identify the best method to estimate q. The adjustment factor (q) is a value used to adjust for probabilities accounting for periods of absolute dryness (PAD). The method should ensure that q is small enough to avoid large alteration of the probabilities regardless of the sample size, increase the positive correlation between rainfall and their SPI, and detect PAD. Results showed that the BD was able to minimise q, and positively increase correlation between rainfall and SPI. Although the PP approach better normalises the SPI, it sometimes underestimates drought intensity. Results also showed that the OM and BD methods have similar behaviour in estimating the probabilities in the absence of PAD. However, during PAD, the BD sufficiently minimises q, consequently not causing large changes in the probabilities of each events.

Key words: *Standardised precipitation index (SPI), Adjustment factor, Periods of absolute dryness*

Introduction

McKee *et al.* (1993) created the Standardised Precipitation Index (SPI) to monitor drought, used in different studies. For example, Hayes *et al.* (1999) used SPI to monitor the 1996 drought in America, and concluded it was able to predict drought at least one-month prior in comparison to the Palmer Drought Severity Index (PDSI). Lana *et al.* (2001) monitored patterns of monthly rainfall shortage and excess in terms of the SPI for Catalonia- Spain. Seiler *et al.* (2002) monitored drought and floods in Argentina, and others monitored drought intensity in Africa and found conclusively that there was a relationship between location and drought variations (Rouault & Richard 2003; Ntale & Gan 2003).

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Methodology

The main objective of this paper is to identify a method that could minimise q, increase the correlation between rainfall events and SPI values, and identify PADs. The study used climate data provided by the South African Weather Services (SAWS) of Alexander Bay and Matiwa, the driest and wettest areas in South Africa respectively, to compute SPI using the Gamma distribution for short terms varying from two to 12 months.

The first step in computing the SPI is to use the Gamma distribution model to generate probabilities G(x), which are later converted using the inverse Gaussian distribution into SPI (McKee *et al.* 1993). Originally, the index did not consider a case when no rainfall occurs, as the Gamma distribution cannot account for the probabilities of zero. To resolve this, Edwards & McKee (1997) suggested the use of adjustment factor q to adjust G(x) when x = 0 to obtain the probability of non-exceedance H(x) (Equation 1):

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

where x is the average rainfall corresponding to a time frame that may vary between two to 12 months referred to as smoothing window. G(x) is the Gamma distribution.

Edwards& McKee (1997) suggest to divide the number of zero by the sample size to estimate q. Ntale & Gan (2003) suggested the use of plotting positions (pp) to estimate q (Equation 2). The pp method is preferable when the time scale is longer than 90 years and requires a different classification method for different smoothing window due to the variability of the sample skewness:

$$q_i = \frac{i - 0.42}{n + 0.3\gamma + 0.05} \quad (2)$$

where i is the rank order of x, n the sample size, γ is the sample skewness when $-3 \leq \gamma \leq 3$.

Due to the shorter time-scale of data, this paper proposes the use of the Binomial distribution (*BD*) to estimate q and a controlling factor (k). In this case, r is the number of zero values in n number of years. K accounts for the number of zero values lost after smoothing by using the size of the smoothing window adding those present in the dataset after smoothing (Equation 3). In addition, given that it can either rain or not, p is set to a half.

Therefore, the adjustment factor becomes as in Equation 9 below:

$$q = \begin{cases} Bin(r,n,p)kn \leq 20;\ r > 0; p = 0.5 \\ Bin(0,n,p)kn \leq 20;\ r = 0; p = 0.5 \end{cases}$$
(3)

The paper compares the three methods of estimating q in order to identify the best method that can improve SPI. Drought contributes negatively to food insecurity, water depletion, health and even the economy. Farmers are usually more vulnerable, especially in rural areas as they have limited resources to withstand the pressure of extreme weather events (Manyever *et al.* 2014). To be able to formulate adequate policies to adapt to drought, it is important to use a method that can differentiate between drought intensities and determine the duration of a drought period.

Results

Table 1 shows correlation results between the SPI generated from G(x), referred to as SPI, and the SPI generated from H(x) using the BD (SPIB), the PP (SPIP), and the OM (SPIO) between two and 12 months. Results revealed that the relationship was consistently stronger between SPI and the SPIB than it was for the other methods for all time frames. Given that q is set to zero for the OM in the absence of PAD, OM becomes irrelevant, thus, making SPIO similar to SPI. However, BD still correlates better with SPI than the PP (**Table 1**). This illustrates that BD is a better method to use in comparison to OM and PP, as it is a better representative of rainfall events.

Table 1: Correlation between the Gamma SPI (GSPI) and the SPIB, SPIP, and the SPIO for Alexander Bay (AB) and Matiwa (MA) (Source: Authors own)

	SPI								
	Months	SPIB	SPIP	SPIO		Months	SPIB	SPIP	SPIO
AB	2	1.000	0.999	0.995	MA	2	1.000	0.997	0.999
	3	1.000	0.998	0.999		3	1.000	0.993	0.998
	4	1.000	0.993	1.000		4	0.996	0.972	1.000
	5	1.000	0.998	1.000		5	1.000	0.997	1.000
	6	1.000	0.938	0.995		6	1.000	0.986	1.000
	12	1.000	0.997	1.000		12	1.000	0.983	1.000

Time series plot of a three month SPI in AB (**Figure 1**) and MA (**Figure 2**) showed that SPIB was able to detect PAD better than SPIO and SPIP, and clearly differentiate between PAD and Periods of Lower Rainfall (PLR). Results also showed that the SPIB described a more intensive drought than the SPIO or the SPIP. For studies focusing on drought classification, all three methods may be acceptable. However, for studies aiming to isolate drought events, investigate their intensity and impact on other variables such as water resources, the *BD* would be the best method.

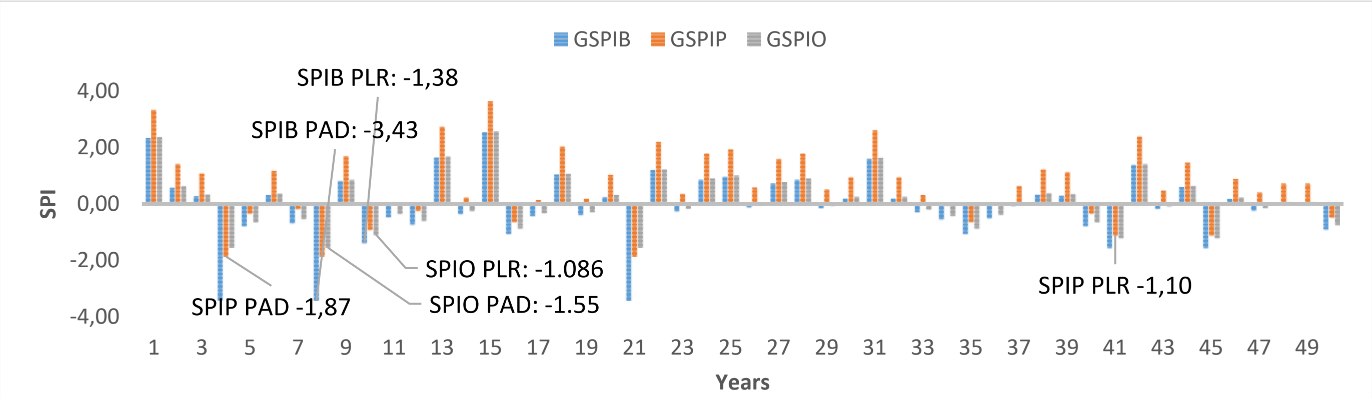

Figure 1: A 3-month time series plot of Alexander Bay over 50 years (Source: Authors own)

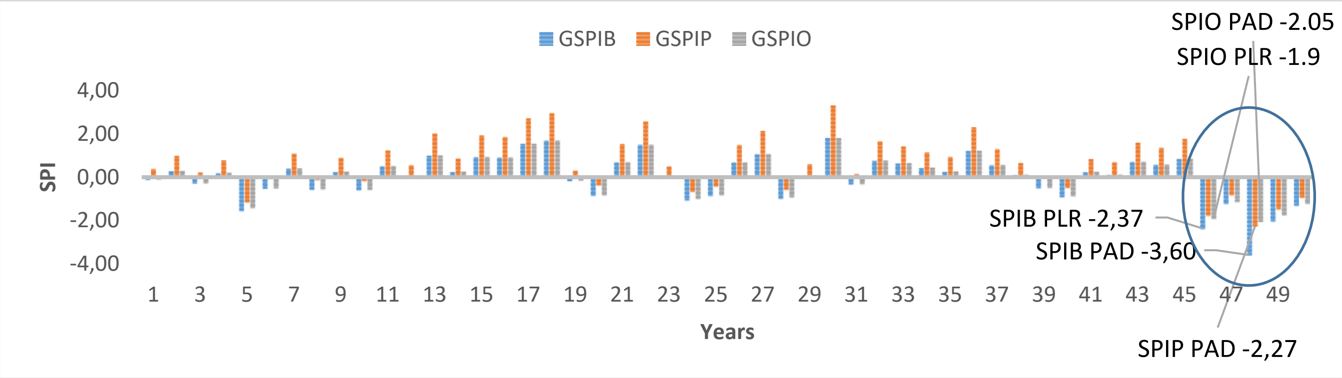

Figure 2: A 3-month time series plot of Matiwa over 50 years (Source: Authors own)

Conclusion

The results proved that the BD was able to minimise *q*, detect PADs, and increase correlation between rainfall and SPI values for short-term drought between two and 12 months better than the PP or the OM. For adaptation and water conservation practices, it is very important to understand the intensity and duration of drought. Climate is rapidly changing around the world, and planning adaptation is a concern in South Africa. IPCC report indicates that climate projections pins extreme weather events. This will affect greatly water resources, infrastructure, health, food security, and the entire ecosystem (Ziervogel *et al.* 2014). Previously, it was proposed that as long as the index falls within the right class it does not matter how low or high the index score is. However, this concept does not take into account intensity and duration of drought (Ntale & Gan 2003). Each weather events influences other variables in a different way. For example, a drought event of -1 would affect water resources differently from a drought event of magnitude -3. The method proposed in this paper addresses drought in terms of intensity and duration, it is able to differentiate between PLR and PAD. This should enable policy makers to track PAD and how they affect the environment. At the same time, take into account other drought events.

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