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AGROMETEOROLOGY - Article

Increasing the regional availability of the Standardized Precipitation Index: an operational approach

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ABSTRACT: The need to use a length of rainfall records of at least 30 years to calculate the Standardized Precipitation Index (SPI) limits its application in several Drought Early Warning Systems of developing countries. Therefore, in order to increase the number of weather stations in which the SPI may be applied, this study quantified the difference among SPI values derived from calibration periods (CP) smaller than 30 years in respect to those computed from the 30-year period of 1985 – 2014 in the State of São Paulo, Brazil (time scales ranging from 1 to 12 months were considered). The correlation, agreement and consistency of SPI values derived from CP ranging from the last 30 to 21 years have been evaluated. The Kolmogorov-Smirnov/Lilliefors test indicated, for all CP, that the 2-parameter gamma distribution may be used to calculate the SPI in the State of São Paulo. The normality test indicated that, even for the period of 1985 – 2014, the normally assumption of the SPI series is not always met. However, it was observed no remarkable difference in the rejection rates of the normality assumption obtained from the different CP. Finally, both absolute mean error and the modified index of agreement indicated a high consistence among SPI values derived from the calibration period of 1991 – 2014 (24 years) in respect to those derived from the 30-year period. Accordingly, it is possible to use weather stations with rainfall records starting in 1991 (or earlier) to calculate, in operational mode, the SPI in the State of São Paulo.

Key words: Drought monitoring, calibration periods, developing countries.

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INTRODUCTION

Drought is a slow-moving hazard that occurs in practically all regions of the Globe (Hayes et al. 2011). The Standardized Precipitation Index (SPI; McKee et al. 1993) has been used to improve the timely detection of emerging droughts (Hayes et al. 1999; Wu et al. 2007; Blain 2012a, among many others) by quantifying, on regional basis, the rainfall departures over a particular time scale. As pointed out by several studies, such as Wu et al. (2007), the SPI has been widely used in both academic and operational modes because it was designed to be a spatially invariant index (Guttman 1999) that quantifies the rainfall deficits in any location and at multiple time scales. The widespread use of this drought index is highlighted by The Lincoln Declaration on Drought Indices (Hayes et al. 2011), which encourages the national meteorological and hydrological services around the world to use the SPI to characterize meteorological droughts. For instance, the SPI is largely used in operational mode by Brazilian agricultural institutions, such as the Brazilian Agricultural Research Corporation (Embrapa), the Agronomic Institute of Campinas (IAC) and the National Institute of Meteorology (INMET) as part of their Drought Early Warning Systems.

The SPI calculation starts by specifying a probability density function (pdf) capable of properly describing the long-term observed precipitation (Guttman 1999). Therefore, the first step of the SPI algorithm is to choose a calibration period (i.e. the length of rainfall records used to calculate this drought index) for fitting the parameters of the pdf. McKee et al. (1993) stated that a continuous period of at least 30 years is required to calculate this index. Unfortunately, it is well-known that this statement has limited the operational application of the SPI in several regions of the world. This fact is particularly true for developing countries such as Brazil, where the lack of long-term meteorological records is a common problem. In this view, the Drought Early Warning Systems of developing countries have been facing the difficult choice of either using only calibration periods equal to or larger than 30 years and applying the SPI in a lower number of locations or using calibration periods lower than 30 years and applying the SPI in a larger number of locations. Therefore, it becomes natural to assume that the scientific literature should address this issue by quantifying the uncertainties associated with the use of length of records lower than 30 years for the SPI calculation.

Wu et al. (2005) evaluated the effect of adopting different lengths of records (or calibration periods) on SPI values. Although this study has used lengths of records equal to or larger than 30 years to calculate the SPI, the authors concluded that SPI values calculated from different lengths of records are highly consistent when there is no significant change on the distribution parameters among the different calibration periods. At this point, it becomes worth mentioning that in general there has been no significant change on the probabilistic structure of the monthly rainfall series of the State of São Paulo (Bardin-Camparotto et al. 2014; Blain et al. 2009) over the last 30 years. Therefore, we pose the following question: regarding the operational mode, is it possible to calculate the SPI for lengths of records smaller than 30 years in the State of São Paulo?

After posing this question, it becomes worth mentioning that, during the early 1990s, the Secretariat of Agriculture and Supply of the State of São Paulo, by means of the Agronomic Institute of Campinas, launched an agrometeorological monitoring program (CIIAGRO/IAC) that has increased the number of meteorological weather stations in the State of São Paulo over (approximately) the last 21 years. Therefore, in order to increase the number of locations of the State of São Paulo where the SPI may be applied, the goal of this study was to quantify the difference among SPI values computed from calibration periods smaller than 30 years in respect to those computed from the so-called standard 30-year calibration period (Stagge et al. 2015). To achieve this goal, the correlation, the agreement and the consistency of SPI values obtained from calibration periods ranging from 30 (1985 – 2014) to 21 (1995 – 2014) years have been evaluated. It is expected that this study will provide a methodological guideline for users who want to increase the regional availability of the SPI.

MATERIAL AND METHODS

The rainfall data were obtained from the Agronomic Institute of Campinas (IAC/APTA/SAA). These weather stations (Table 1) have been selected because they present no missing values and their consistency has already been evaluated in previous studies (Bardin-Camparotto et al. 2014; Blain et al. 2009). These weather stations also represent climatically dissimilar areas of the State, ranging from the coastal area (Ubatuba), where there is no distinctly dry season, to the northwestern region of the State (Ribeirão Preto), where there is a distinctly dry season during the winter months (see Appendices 1 and 2).

Table 1. Weather stations used to calculated the Standardized Precipitation Index (State of São Paulo, Brazil).

	Latitude (S)	Longitude (W)	Altitude (m)
Campinas	22°54′	47°05′	669
Jundiaí	23°07′	47°43′	538
Mococa	21°27′	46°59′	665
Monte Alegre do Sul	22°42′	46°39′	777
Pariquera-Açu	24°43′	47°52′	68
Pindorama	21°13′	48°54′	562
Ribeirão Preto	21°11′	47°48′	620
Ubatuba	23°26′	45°3′	5

As described, the SPI can be computed for multiple time scales depending on the user's interest, with typical values ranging from 1 to 12 months (Blain 2012b; Dutra et al. 2013). The time scales of 1, 3, 6, 9 and 12 months have been adopted because they are used in operational mode by the Drought Monitoring System of IAC/CIIAGRO.

Although several pdfs may be used to calculate the SPI (Guttman 1999), the 2-parameter gamma distribution is the most used (Wu et al. 2005; Wu et al. 2007; Dutra et al. 2013; Stagge et al. 2015). Once a pdf is chosen (Equation 1), the cumulative probability [H(PRE)] of a given rainfall amount is obtained from Equations 2 and 3, in which the lower limit of the integral is zero because the precipitation distributions are zero-bounded) — q is the number of zeros in the data sample. As described by several studies, such as Wu et al. (2007), the final step of the SPI algorithm is based on the rational approach proposed by Abramowitz and Stegun (1965; Equations 4 and 5).

$$\mathrm{gam(PRE)} = \frac{\mathrm{PRE}^{\alpha-1} \cdot e^{-\mathrm{PRE}/\beta}}{\beta^{\alpha}\,\Gamma(\alpha)} \quad \mathrm{PRE}, \alpha, \beta > 0 \tag{1}$$

where: $\Gamma(\alpha)$ is the gamma function; α and β are the distribution parameters; PRE is the rainfall amounts.

$$\mathrm{Gam(PRE)} = \int_0^{\mathrm{PRE}} \mathrm{gam(PRE)d(PRE)} \tag{2}$$

$$\mathrm{H(PRE)} = q + (1 - q)\mathrm{Gam(PRE)} \tag{3}$$

$$\mathrm{SPI} = -\left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \text{ for } 0 < \mathrm{H(PRE)} \le 0.5$$
$$\mathrm{SPI} = -\left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \text{ for } 0.5 < \mathrm{H(PRE)} < 1 \tag{4}$$

$$t = \sqrt{\left(\ln\left(\frac{1}{(\mathrm{H(PRE)})^2}\right)\right)} \text{ for } 0 < \mathrm{H(PRE)} \le 0.5$$
$$t = \sqrt{\left(\ln\left(\frac{1}{(\mathrm{H(PRE)})^2}\right)\right)} \text{ for } 0.5 < \mathrm{H(PRE)} < 1 \tag{5}$$

where: $c_0 = 2.515517$; $c_1 = 0.802853$; $c_2 = 0.010328$; $d_1 = 1.432788$; $d_2 = 0.189269$; $d_3 = 0.001308$.

The SPI wet/drought categories are presented in Table 2. The frequently used Kolmogorov-Smirnov/Lilliefors test (KSL; Wilks 2011) was applied to assess the fit of the gamma distribution to the rainfall data obtained from all calibration periods. The Monte Carlo simulations required for calculating the critical values of this goodness-of-fit test were based on the procedure called "Non-uniform random number generation by inversion" (Wilks 2011; Blain 2014, among many others). Further information on this test, including its advantages over other goodness-of-fit tests, can be found in several studies such as Wilks (2011). The KSL

Table 2. Standardized Precipitation Index values and the associated drought categories.

SPI values	Drought category
≥ 2.00	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
0.99 to −0.99	Near normal
−1.00 to −1.49	Moderately dry
−1.50 to −1.99	Severely dry
≤ −2.00	Extremely dry

SPI = Standardized Precipitation Index. Extracted from the Standardized Precipitation Index User Guide: WMO Nº1090. www.wamis.org/agm/pubs/SPI/WMO_1090_EN.pdf test was calculated at the 5% significance level by means of an r-code (R-software) adapted from Blain (2014; Appendix 3).

As previously described, the SPI was designed as a spatially invariant drought index (Guttman 1999). In other words, a SPI series must be capable of meeting the normality assumption (Wu et al. 2007; Blain 2012a,b; Stagge et al. 2015). Therefore, we applied an algorithm proposed by Wu et al. (2007) to verify the normality assumption of the SPI series derived from the different calibration periods evaluated in this study. According to this algorithm, a SPI series is considered non-normal when the 2 following criteria are simultaneously met: (1) absolute value of the median greater than 0.05; (2) Shapiro-Wilk's (SW) statistic test lower than 0.96 and p-values ≤ 0.10. For further information on the Shapiro-Wilk's test, see Razali and Wah (2011).

The degree of correlation among the SPI values obtained from the different calibration periods was initially evaluated by means of the linear correlation analysis as suggested by Wu et al. (2005). However, it is well-known that the magnitude of the r^2 coefficient is not consistently related to the degree to which SPI values, derived from different sample sizes, approach each other (Willmott 1982; Wu et al. 2005, among many others). This degree of accuracy (or agreement) was measured by the modified index of agreement (d_{mod}; Willmott et al. 1985) and by the absolute mean error (AME), which can be thought as a scalar measurement of the average difference between 2 datasets (Wilks 2011). The d_{mod} is bounded by 0 and 1. A perfect fit between SPI values obtained from the 30-year calibration period in respect to those derived from other calibration periods (< 30 years) would lead to $d_{mod} = 1$. When applied to a given data bunch, the d_{mod} will be lower or, at most, equal to the original index of agreement (further information regarding the difference between the original index of agreement and its modified version can be found in Willmott et al. 1985). Quantitative estimates of both systematic and random errors were made according to Equations 6 and 7, respectively (Willmott 1982):

$$MSE_s = N^{-1} \sum_{i=1}^{N} (\hat{P}_i - O_i)^2 \quad (6)$$

$$MSE_r = N^{-1} \sum_{i=1}^{N} (\hat{P}_i - \hat{P}_i)^2 \quad (7)$$

where: N is the sample size; O is the SPI value calculated from the standard 30-year period (1985 – 2014); P is the SPI value calculated from calibration periods smaller than 30 years; $\hat{P}$ represents the predicted SPI values according to the linear regression equation; MSE_s and MSE_r are, respectively, the systematic and random components of the error.

Finally, as an operational assessment of the consistency of the SPI values derived from different calibration periods, all SPI monthly values observed during 2013 and 2014 have been compared in respect to their wet/drought categories (Table 2). This qualitative assessment is similar to those found in Wu et al. (2005). These 2 years (2013 and 2014) have been selected because, since 2013, the State of São Paulo has been subjected to an extreme/severe drought event (as shown in the next section).

RESULTS AND DISCUSSION

Before analyzing the results of the KSL test (Table 2), it has to be emphasized that several 3-parameter distributions, such as generalized normal distribution (Meschiatti and Blain 2015) and Pearson's type III (Guttman 1999; Vicente-Serrano et al. 2012; Blain 2012b), have also been recommended to calculate the SPI because they are more flexible than the 2-parameter gamma. However, Stagge et al. (2015) remind that a 3-parameter distribution allows negative values. Naturally, when these functions are used in studies dealing with rainfall series, they must be truncated at zero. In addition, Stagge et al. (2015) are of the opinion that adding an extra parameter is an unnecessary complication given the relative small sample sizes (or calibration periods) that are frequently used to calculate the SPI. The results of the KSL test (Table 3) agree with these latter statements, given that the average acceptance rates of the gamma distribution were higher than 92% for all calibration periods and time scales.

The acceptance rates presented in Table 3 are also consistent with those found by Stagge et al. (2015), who, as previously described, recommended the use of gamma distribution to calculate the SPI throughout Europe. Therefore, we may state that the KSL test has provided evidences in favor of the use of gamma distribution to calculate the SPI in the State of São Paulo. However, in spite of the fact that this latter statement holds for all calibration periods evaluated in Table 3 (21 to 30 years), it has to be emphasized that the KSL is a relatively insensitive test because both empirical and theoretical distributions converge to zero and/or one in their tails (Stagge et al. 2015; Kruel et al. 2015). This statement is consistent with the fact that the acceptance rates of the normality test (Table 4) are lower than those of the KSL test. This fact is also consistent with the results presented by Stagge et al. (2015) for Europe, where the rejection rates of the KSL test were, on average, 7% lower than those of the Shapiro-Wilk's test.

The results presented in Table 4 indicate that, even for the 30-year period, the normally assumption is not always met. In other words, even those SPI series calculated from the continuous 30-year period recommended by McKee et al. (1993) and regarded by Stagge et al. (2015) as "the standard period for the SPI calculation" are not always capable of meeting the assumption of normality. This statement is particular true for the monthly time scale and may be explained by the presence of zero values in the rainfall series (see Appendix 2) that leads the SPI to be a lower bounded index (Wu et al. 2007; Blain 2012a; Stagge et al. 2015). This statement is also the reason why Wu et al. (2007) recommended that the SPI user be cautious when using this drought index at short-time scales. By analyzing the results presented in Table 4, one is also able to verify that the rejection rates of the normality test observed in this study (which varied from 2 to 20%) are, in general, lower than those found by Stagge et al. (2015). According to these authors, in some regions of Denmark, France and Greece, the normality assumption of the SPI series (calculated from the gamma distribution) varied from 15 to 40%.

By considering the general goal of this study (i.e. the operational use of the SPI), the results presented in Table 4 do not indicate remarkable differences among the rejection/ →

Table 3. Average acceptance rates (%) of the gamma distribution to fit rainfall amounts accumulated over 1; 3; 6; 9 and 12 months. The acceptance rates have been obtained by applying the Kolmogorov-Smirnov/Lilliefors test (5% significance level) to 9 locations of the State of São Paulo, Brazil.

Period	1-month	3-month	6-month	9-month	12-month
1985 – 2014	95.2	94.0	91.7	90.5	92.9
1986 – 2014	92.9	92.9	94.0	94.0	92.9
1987 – 2014	95.2	91.7	96.4	96.4	96.4
1988 – 2014	96.4	94.0	92.9	96.4	94.0
1989 – 2014	95.2	96.4	95.2	97.6	96.4
1990 – 2014	96.4	97.6	96.4	95.2	96.4
1991 – 2014	97.6	96.4	96.4	96.4	97.6
1992 – 2014	97.6	98.8	98.8	96.4	97.6
1993 – 2014	92.9	90.5	94.0	94.0	90.5
1994 – 2014	94.0	95.2	94.0	96.4	96.4

Table 4. Average acceptance rates (%) of the normally assumption of Standardized Precipitation Index series calculated at the following time scales: 1; 3; 6; 9 and 12 months. The acceptance rates have been obtained by applying a normality test, proposed by Wu et al. (2007), to 9 locations of the State of São Paulo, Brazil.

Period	1-month	3-month	6-month	9-month	12-month
1985 – 2014	86	93	95	96	93
1986 – 2014	83	90	95	92	93
1987 – 2014	87	93	94	90	90
1988 – 2014	80	93	98	92	86
1989 – 2014	88	93	95	93	89
1990 – 2014	85	92	94	92	85
1991 – 2014	86	92	96	90	85
1992 – 2014	83	93	95	94	87
1993 – 2014	82	92	96	89	89
1994 – 2014	82	90	96	92	85

acceptance rates obtained from the different calibration periods. For instance, the average acceptance rate of the monthly SPI series derived from the 30-year and 21-year periods are, respectively, 86 and 82%. The great difference among the acceptance rates is observed for the 12-month SPI series in which the acceptance rate varied from 93% (30 years) to 85% (21 years). Therefore, regarding the normality assumption, the results presented in Table 4 indicated that the performance of the SPI series derived from the smallest calibration period (21 years, 1994 – 2014) was equivalent to the performance of the SPI series obtained from the 30-year period of 1985 – 2014 in 93% of the cases (at least). The results presented in Tables 3, 4 allowed us to quantify the correlation, the agreement and the consistency of SPI values obtained from the calibration periods ranging from 29 to 21 years in respect to the SPI values obtained from the standard 30-year period.

The linear correlation analysis indicated a lack of random errors among the SPI values obtained from the 30-year period in respect to those obtained from other (smaller) lengths of records. As exemplified in Figure 1, for the weather station of Campinas (monthly SPI values, considering the 30-year and 21-year calibration periods), the linear correlation analysis reveals that using calibration periods smaller than 30 years to calculate the SPI leads to non-random error. This statement is also supported by the MSE_r and MSE_s values presented in Figure 1. As can be noted, only the systematic component of the MSE is greater than zero. The results of all other regression analyses were equivalent to those depicted in Figure 1.

Similar to the results found by Wu et al. (2005), the AME values increased as the length of the calibration periods decreased (Figure 2). For instance, no AME > 0.1 was observed for calibration periods equal to or larger than 27 years. On the other hand, the highest AMEs are observed for the smallest calibration periods (22 and 21 years). For these periods, AME has reached values greater than 0.25. By considering that 0.5 is the numerical difference between a severe and an extreme drought event (Table 2), these latter AME values suggest that calibration periods starting after 1991 should not be used to derive SPI values in the State of São Paulo. This latter inference is consistent with the results depicted in Figure 3. By following Wu et al. (2005), we may assume that values of d_{mod} equal to or greater than 0.90 describe a high (and acceptable) agreement between 2 SPI series derived from different calibration periods. In this view, no d_{mod} < 0.9 is observed for calibration periods starting in 1991 (or earlier; Figure 3).

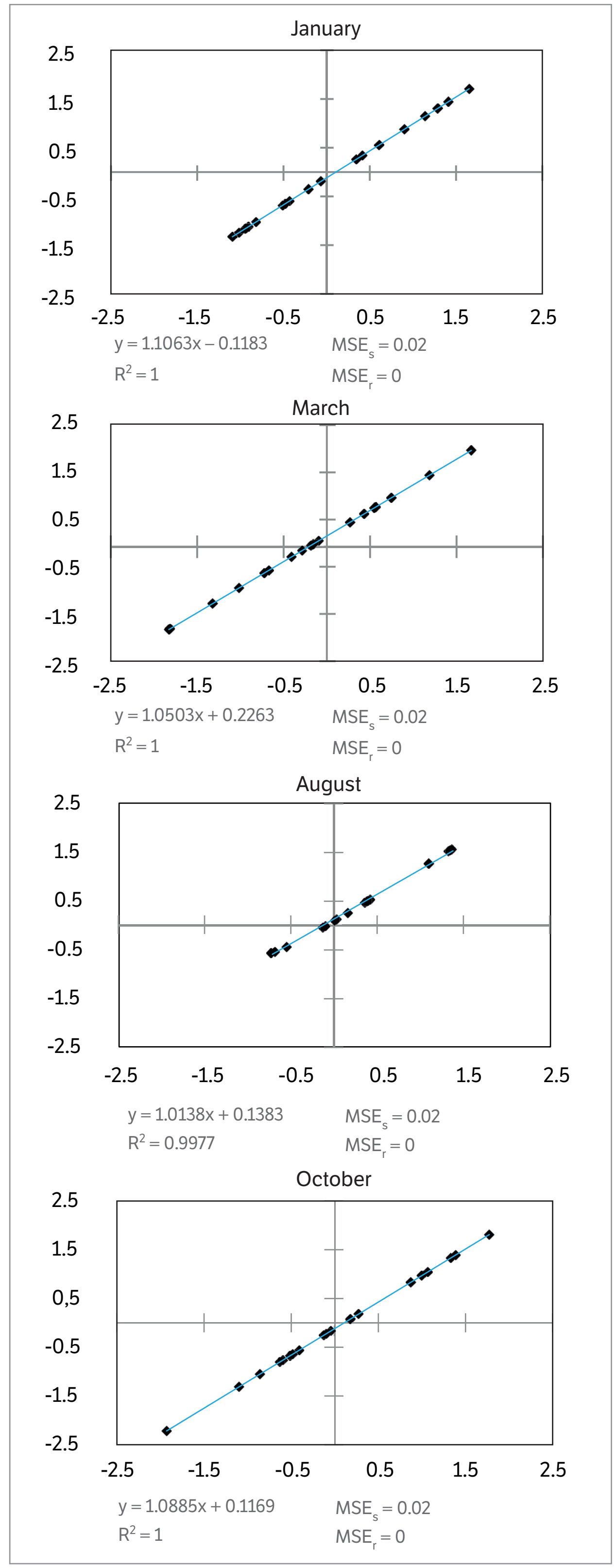

Figure 1. Linear regression analysis — Standardized Precipitation Index monthly values for 1985 – 2014 (x-axis) and Standardized Precipitation Index monthly values for 1994 – 2014 (y-axis). Campinas, State of São Paulo.

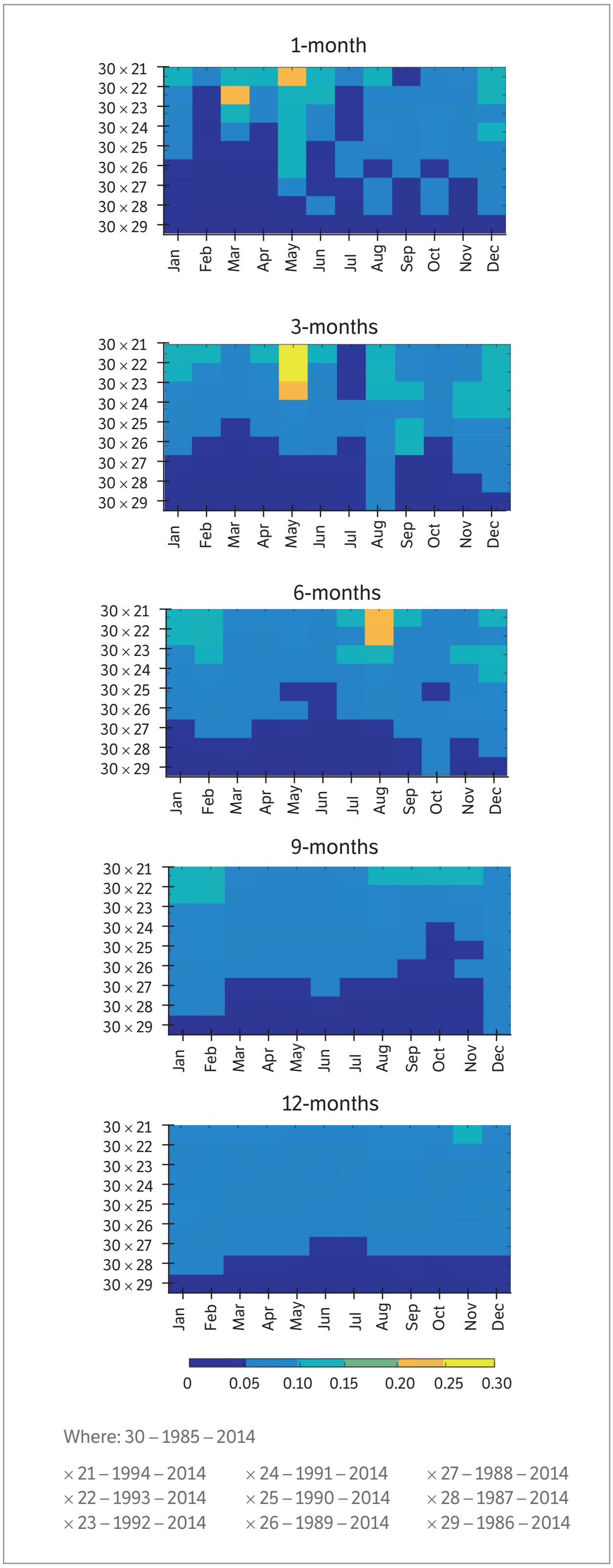

Figure 2. Absolute mean error of Standardized Precipitation Index values derived from calibration periods ranging from 1994 – 2014 to 1986 – 2014 (21 to 29 years) in respect to Standardized Precipitation Index values derived from 1985 – 2014. State of São Paulo, Brazil.

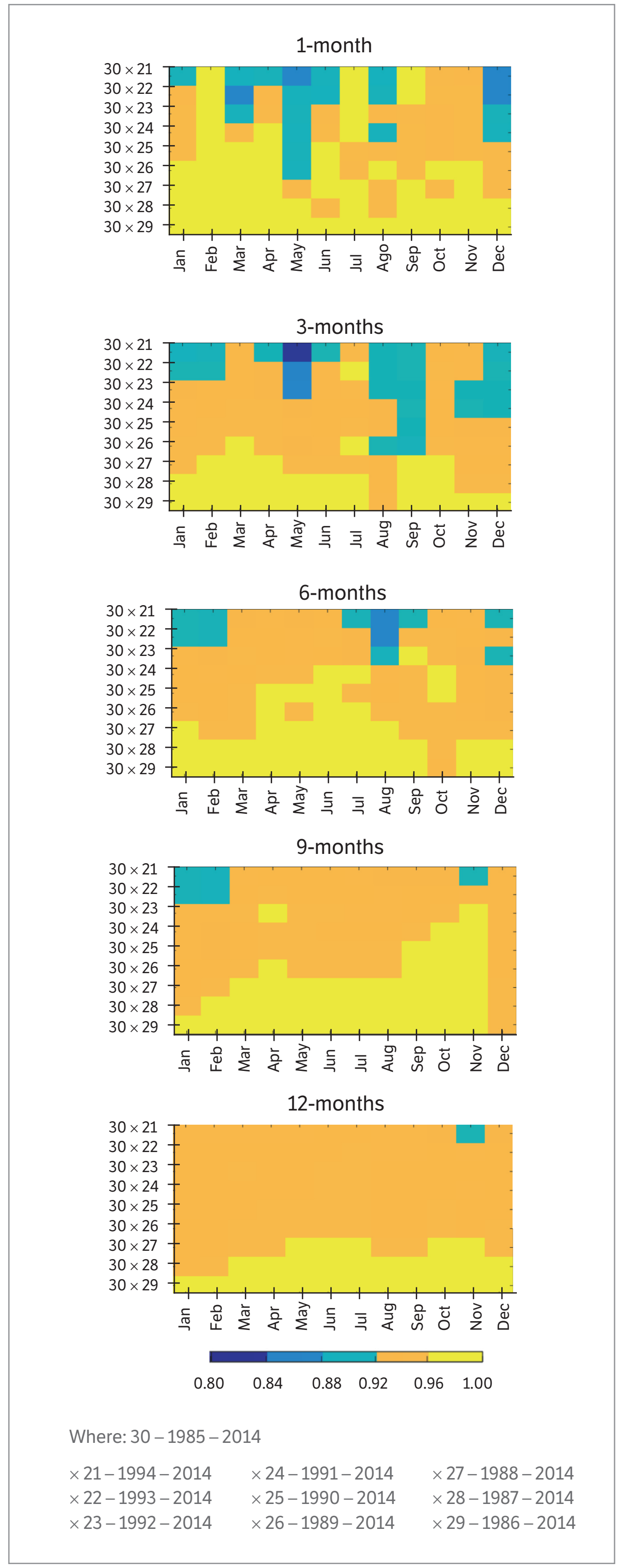

Figure 3. Modified index of agreement (d_{mod}) of Standardized Precipitation Index values derived from calibration periods ranging from 1994 – 2014 to 1986 – 2014 (21 to 29 years) in respect to Standardized Precipitation Index values derived from 1985 – 2014. State of São Paulo, Brazil.

Considering that SPI values calculated from different lengths of records are highly consistent and correlated only when the parameters of the gamma distributions are similar (Wu et al. 2005), the results of Figures 2, 3 (and the conclusion drawn from them) suggest a change in the rainfall distributions after 1991. Indeed, by evaluating the parameters of this distributions calculated from the monthly series, we observed a remarkable change around 1992 – 1993, as exemplified for the Weather Station of Campinas (Figure 4). Note that this last statement is particular true for the 8 of the 12 monthly series (January; February; March; April; May; June; July and November).

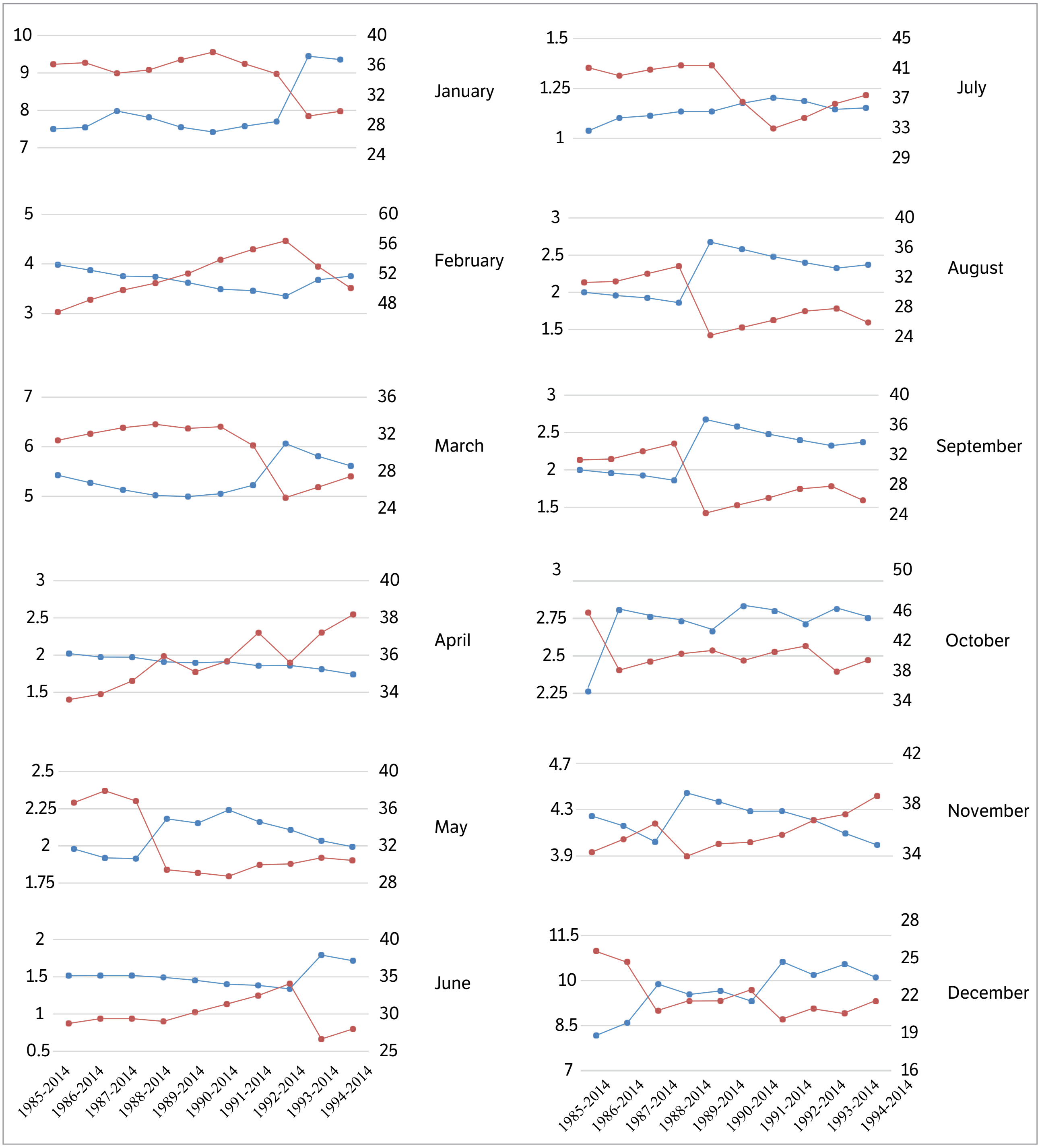

Figure 4. Shape (blue line) and scale (red line) of the gamma distribution calculated from different lengths of rainfall records (Campinas, São Paulo, Brazil).

Case of study (operational mode)

Under the operational mode and regarding the question posed at the beginning of this study, the above-mentioned results allows us to infer that there will be no remarkable difference in the wet/dry SPI categories (Table 2) derived from calibration periods ranging from 1991 – 2014 to 1986 – 2014 in respect to those derived from 1985 – 2014 in the State of São Paulo. The visual inspection of Figures 5 to 9 supports this inference by describing virtually no difference in the wet/dry categories characterized by SPI values derived from the smallest selected period (24 years; 1991 – 2014) in respect to the standard 30-year period of 1985 – 2014.

Regardless the calibration period, the results depicted in Figure 5 (monthly SPI) clearly indicate that 2014 has started under severe to extreme dry conditions (SPI < −2.0). The results depicted in Figure 5, along with those depicted in Figures 6 to 9, support the idea that the State of São Paulo has been subjected to a drought event expected to occur once, on average, 100 – 700 years. The analysis of Figures

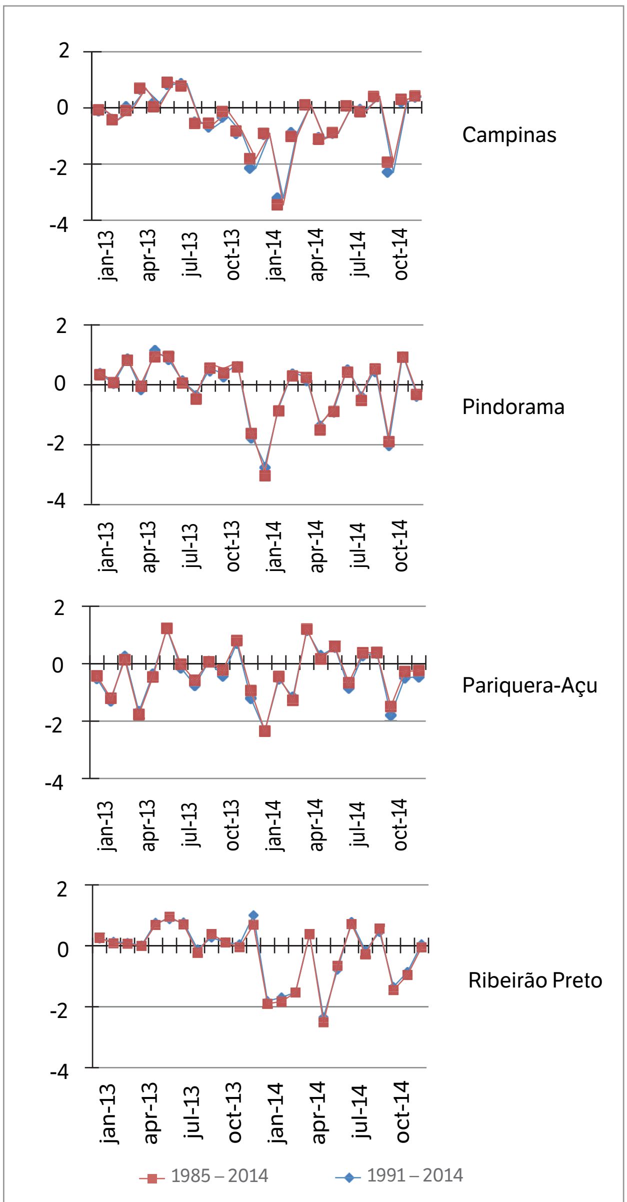

Figura 5. Standardized Precipitation Index derived from different calibration periods (time scale: 1-month) for 4 locations of the State of São Paulo.

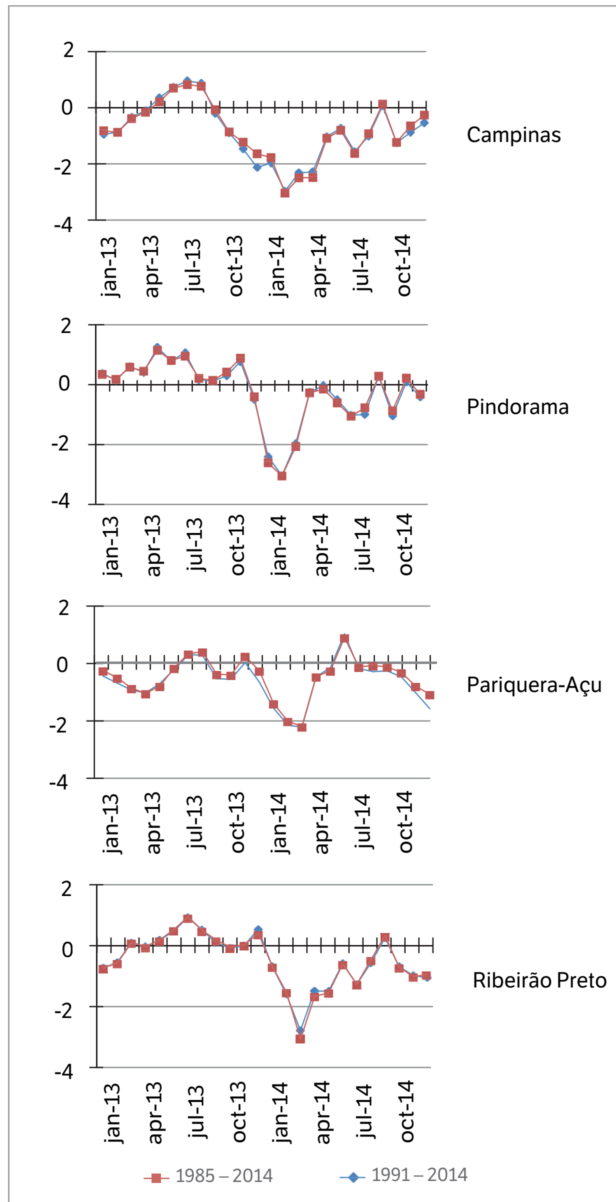

Figure 6. Standardized Precipitation Index derived from different calibration periods (time scale: 3-month) for 4 locations of the State of São Paulo.

4 to 8 also emphasizes the importance of monitoring the rainfall deficits at several time scales for detecting the onset of a drought as soon as possible (Hayes et al. 1999). In spite of the negative values depicted in Figure 5 (monthly SPI), it is not evident that a drought has been established. For instance, the monthly SPI value for January, 2014 (Pindorama, São Paulo) is –2.70 (1991 – 2014) or –3.20 (1985 – 2014). However, in March, 2014 this index has reached the near normal category by presenting values equal to 0.44 (calibration periods: 1991 – 2014) or 0.39 (calibration periods: 1985 – 2014; Figure 5). On the other hand, by analyzing this index at larger time scales (e.g. 6 to 12 months), one is able to verify that no positive SPI value has been recorded after January, 2014. Naturally, these negative SPI values observed at all time scales (Figures 4 to 8) indicate that a severe to extreme drought has been established in the State of São Paulo since January, 2014. This latter inference can be drawn from the SPI values derived from the 30-year period of 1985 – 2014 as well as from SPI values derived from the 24-year period of 1991 – 2014.

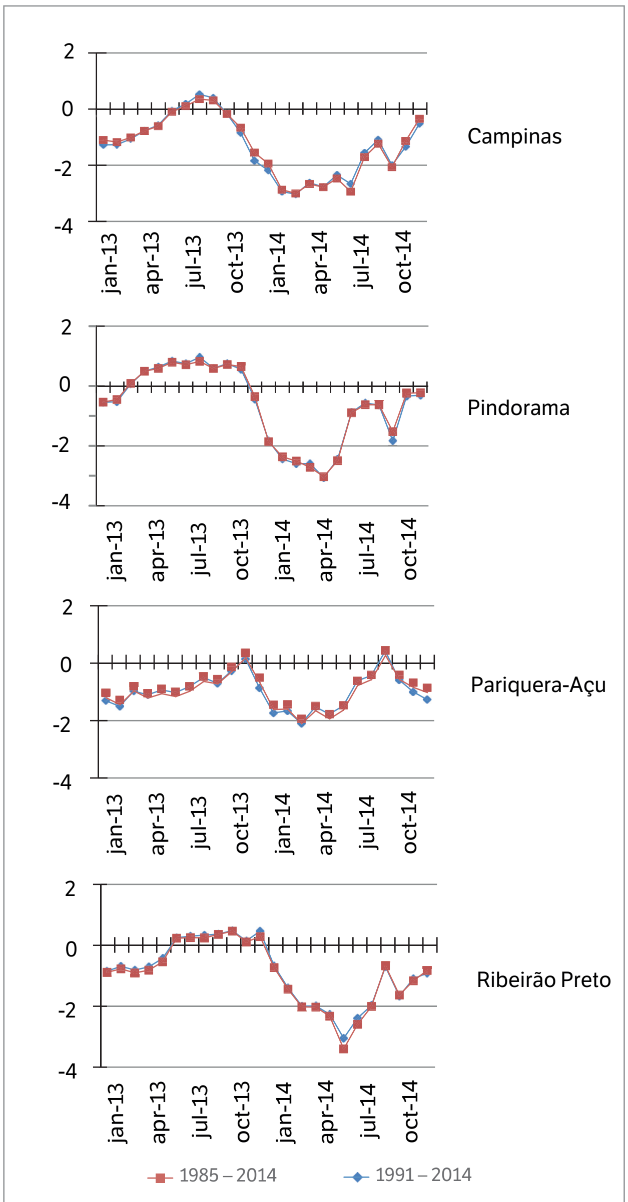

Figure 7. Standardized Precipitation Index derived from different calibration periods (time scale: 6-month) for 4 locations of the State of São Paulo.

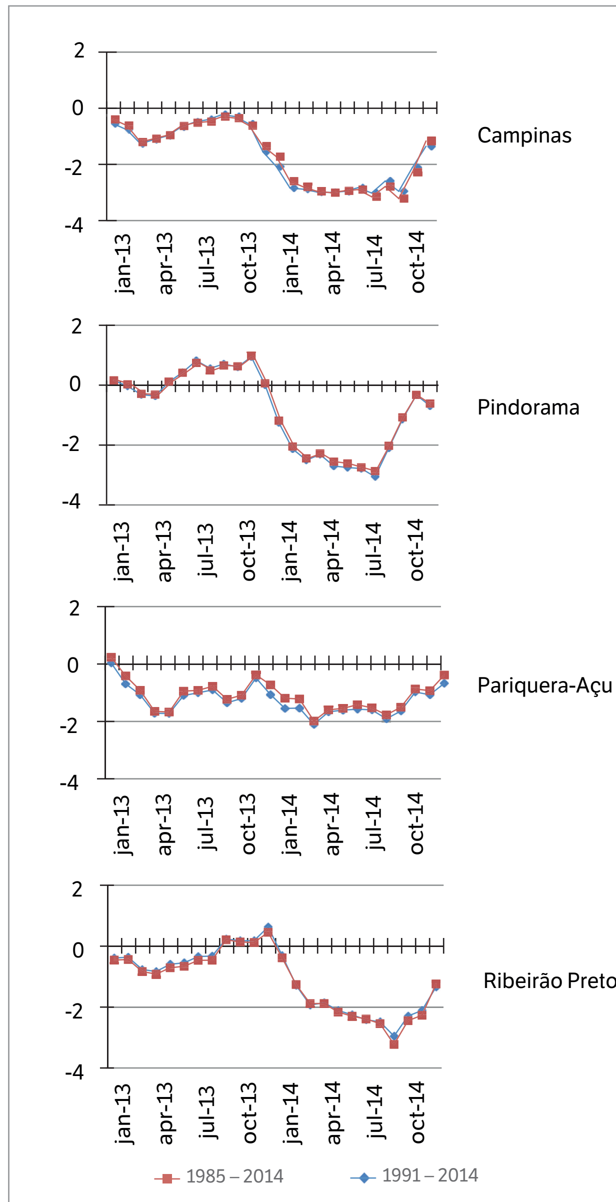

Figure 8. Standardized Precipitation Index derived from different calibration periods (time scale: 9-month) for 4 locations of the State of São Paulo.

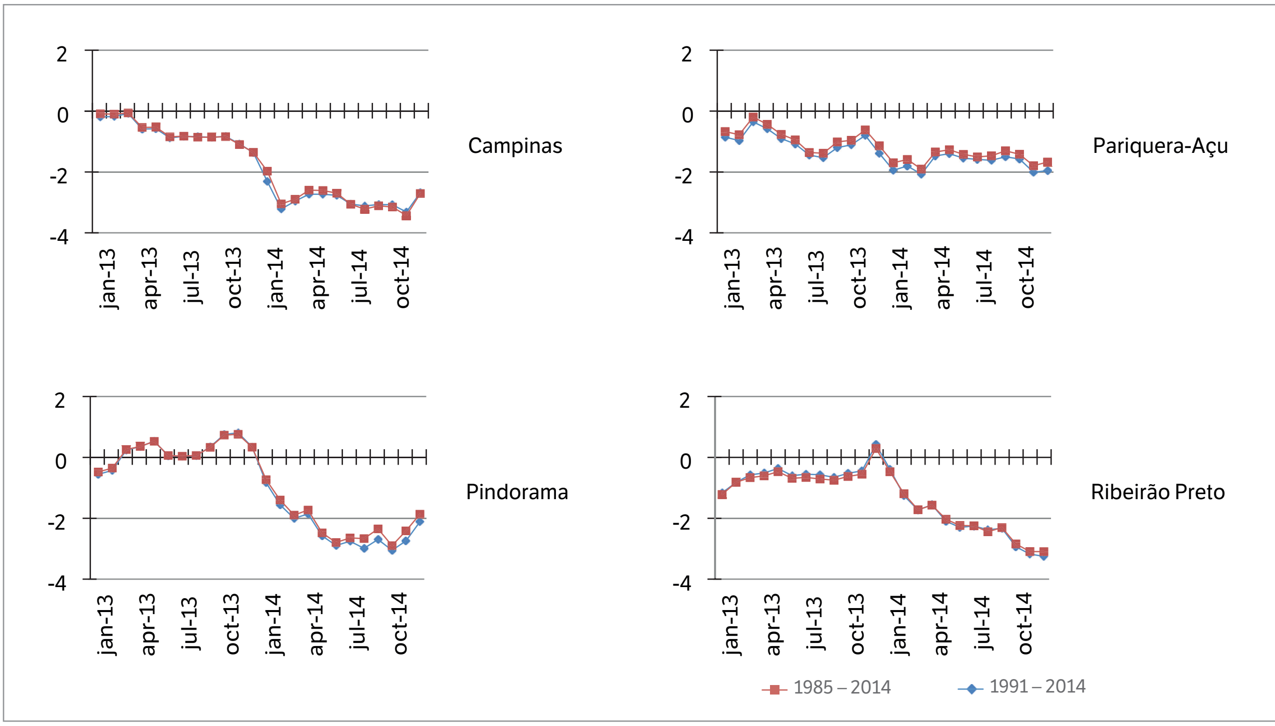

Figure 9. Standardized Precipitation Index derived from different calibration periods (time scale: 12-month) for 4 locations of the State of São Paulo.

CONCLUSION

There is high agreement among SPI values derived from the calibration period of 1985 – 2014 (30-year period) in respect to those SPI values derived from calibration periods ranging from 1991 – 2014 to 1986 – 2014. This conclusion allows using weather stations with rainfall records starting in 1991 (or earlier) for the operational application of the Standardized Precipitation Index in the State of São Paulo, Brazil. This conclusion is based on evaluations of intrinsic features of the SPI. Therefore, the methods used in this study may be used to increase the regional availability of the Standardized Precipitation Index in any area of the globe.

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Appendix 1. Shape and scale parameters of the gamma distribution (8 locations of the State of São Paulo; 1985 – 2014).

Month	Campinas		Jundiaí		Mococa		Monte Alegre do Sul	
	Shape	Scale	Shape	Scale	Shape	Scale	Shape	Scale
Jan	7.5	36.1	4.7	59.8	5.9	49.9	4.6	61.3
Feb	4.0	46.9	7.8	23.3	3.9	50.1	4.1	47.8
Mar	5.4	31.4	3.6	46.6	5.0	33.3	6.4	29.3
Apr	2.0	34.5	2.7	26.8	1.6	55.7	2.8	31.8
May	2.0	36.6	2.0	38.5	1.9	36.5	1.9	39.1
Jun	1.3	32.8	1.2	41.7	0.9	33.3	1.1	43.7
Jul	1.0	41.1	1.0	54.7	1.1	22.5	1.1	41.4
Aug	1.2	26.9	0.9	38.6	0.9	34.9	0.9	40.0
Sep	2.0	31.3	1.5	48.3	2.0	32.4	2.9	27.4
Oct	2.3	45.8	2.9	41.0	3.1	42.6	2.5	56.1
Nov	4.2	34.0	4.6	34.6	7.5	22.5	5.8	27.8
Dec	8.2	25.6	5.3	38.8	10.1	25.8	9.1	24.8
Month	Pariquera-Açu		Pindorama		Ribeirão Preto		Ubatuba	
	Shape	Scale	Shape	Scale	Shape	Scale	Shape	Scale
Jan	4.9	54.8	5.9	47.0	6.0	46.2	6.5	49.1
Feb	5.7	41.0	4.0	52.3	3.3	66.5	2.7	108.6
Mar	6.9	31.8	4.3	36.9	5.9	28.3	3.7	85.9
Apr	4.8	21.0	3.5	23.5	1.4	52.4	2.9	80.0
May	2.6	34.7	1.6	39.7	1.2	52.3	4.5	29.5
Jun	2.0	37.4	0.6	49.2	0.6	46.7	1.9	43.5
Jul	1.8	49.8	0.9	28.8	0.9	26.8	2.3	45.1
Aug	1.6	31.4	0.8	47.1	0.6	53.6	2.7	27.6
Sep	2.1	51.6	1.2	52.0	1.0	56.4	6.5	27.7
Oct	5.6	21.1	2.6	38.4	3.7	27.1	5.0	47.3
Nov	3.6	29.8	4.7	29.0	6.0	30.2	6.1	40.3
Dec	7.3	23.9	6.7	31.1	7.2	35.4	5.2	56.8

Appendix 2. Average rainfall amounts and frequency of zero rainfall values. State of São Paulo (1985 – 2014).

	Campinas		Cordeirópolis		Mococa		Monte Alegre do Sul	
	Pre	% Pre = 0	Pre	% Pre = 0	Pre	% Pre = 0	Pre	% Pre = 0
Jan	261.8	0.0	251.3	0.0	279.1	0.0	267.5	0.0
Feb	180.9	0.0	180.0	0.0	193.7	0.0	195.8	0.0
Mar	157.1	0.0	162.7	0.0	157.2	0.0	167.9	0.0
Apr	73.8	0.0	78.7	0.0	84.8	0.0	87.7	0.0
May	70.9	0.0	61.7	0.0	64.1	0.0	70.5	0.0
Jun	49.3	8.9	48.2	8.9	34.2	15.6	52.3	6.7
Jul	39.4	8.9	35.1	6.7	26.2	11.1	41.3	8.9
Aug	30.8	17.8	28.9	26.7	24.6	26.7	34.5	15.6
Sep	67.7	2.2	67.5	4.4	70.6	2.2	76.2	2.2
Oct	112.6	0.0	112.5	0.0	125.2	0.0	129.8	0.0
Nov	144.4	0.0	155.6	0.0	181.1	0.0	165.5	0.0
Dec	212.6	0.0	218.6	0.0	269.3	0.0	233.8	0.0
	Pariquera-Açu		**Pindorama**		**Ribeirão Preto**		**Ubatuba**	
	Pre	**% Pre = 0**	**Pre**	**% Pre = 0**	**Pre**	**% Pre = 0**	**Pre**	**% Pre = 0**
Jan	238.3	0.0	269.1	0.0	275.3	0.0	330.6	0.0
Feb	206.0	0.0	197.9	0.0	214.5	0.0	259.8	0.0
Mar	211.2	0.0	161.0	0.0	160.8	0.0	265.9	0.0
Apr	99.0	0.0	81.1	4.4	84.2	0.0	203.1	0.0
May	91.9	0.0	61.9	0.0	61.6	0.0	112.3	0.0
Jun	72.3	0.0	35.5	15.6	35.4	17.8	79.8	0.0
Jul	66.6	2.2	28.6	17.8	27.5	13.3	82.6	2.2
Aug	50.8	4.4	26.2	24.4	23.5	31.1	72.8	4.4
Sep	98.4	0.0	63.2	4.4	60.6	0.0	165.8	0.0
Oct	108.7	0.0	106.1	0.0	117.2	0.0	201.0	0.0
Nov	120.5	0.0	142.4	0.0	178.0	0.0	237.3	0.0
Dec	174.0	0.0	223.9	0.0	269.8	0.0	283.5	0.0

Pre = Average rainfall amounts; % Pre = 0 = Frequency of zero rainfall values.

Appendix 3. R-code (R-software) adapted from Blain (2014).

```
################
# datamatrix is a matrix in which each column corresponds to each month
#As can be observed in this code all years must present 12 rainfall amounts
datamatrix= as.matrix(read.table("datamatrix.txt", head=T))
shape=matrix(NA,12,1)
scale=matrix(NA,12,1)
Dmax=matrix(NA,12,1)
NKSLcrit5=matrix(NA,12,1)
NKSLcrit10=matrix(NA,12,1)
pvalue=matrix(NA,12,1)
for (month in 1:12){
data=datamatrix[,month]
data1=data> 0
datap=data[data1] # the 2-parameter gamma is undefined for x < 0
n=length(data)
np=length(datap)
nz=n-np
probzero=(n-nz)/n
Ns=50000
probacum=matrix(NA,np,1)
lilliefors=matrix(NA,Ns,1)
probpar= matrix(NA,np,1)
A=log(mean(datap))-((sum(log(datap)))/np)
shape[month,1]=(1/(4*A))*(1+sqrt(1+(4*A/3)))
scale[month,1]=mean(datap)/shape[month,1]
pos=matrix(1:np, np, 1)/np
probacum[,1]= (pgamma(sort(datap), shape[month,1], 1/scale[month,1], lower.tail = TRUE, log.p = FALSE))
Dmax[month,1]=max(abs(pos- probacum))
########Lilliefors
x=matrix(NA,np,1)
lilliefors=matrix(NA,Ns,1)
probpar=matrix(NA,np,1)
poss=matrix(1: np, np, 1)/np
for (i in 1:Ns){
x[,1]=rgamma(np,shape[month,1],1/scale[month,1])
As=log(mean(x))-((sum(log(x)))/np)
alfals=(1/(4*As))*(1+sqrt(1+(4*As/3)))
betals=mean(x)/alfals
probpar[,1]=pgamma(sort(x), alfals, 1/betals, lower.tail = TRUE, log.p = FALSE)
Dmaxs=max(abs(poss- probpar))
lilliefors[i,1]=Dmaxs}
NKSLcrit5[month,1]=quantile(lilliefors, probs=0.95)
NKSLcrit10[month,1]=quantile(lilliefors, probs=0.90)
m=lilliefors>Dmax[month,1]
pvalue[month,1]=(length(lilliefors[m]))/Ns}
Goodness=c("shape", shape, "scale", scale, "Dmax", Dmax, "NKSLcrit5%",    NKSLcrit5, "NKSLcrit10%", NKSLcrit10, "p-value", pvalue)
write.csv(Goodness, "GoodnessGamma.csv")
##############
```