INCREASES IN THE FREQUENCY OF METEOROLOGICAL DROUGHTS IN THE STATE OF SÃO PAULO, BRAZIL, UNDER CLIMATE CHANGE CONDITIONS

Letícia Lopes Martins

Graciela da Rocha Sobierajski

Gabriel Constantino Blain

ABSTRACT

Climate changes are often regarded as the major factor leading to the observed increases in drought frequency and intensity worldwide. Considering the negative effects triggered by this environmental hazard, the goal of this study was to detect and quantify changes in the probability of drought events in the State of São Paulo, Brazil. The study was based on rainfall data from the NASA-POWER project, which is capable of providing meteorological series with more than 30 years of record. The drought events were quantified through the Standardized Precipitation Index (SPI), which was calculated by means of a probability-based nonstationary method designed to improve the interpretation of the index estimates under climate change conditions. The results found in this study indicated that the frequency of meteorological droughts has increased over the last years. This statement is particularly true for the months of March and April (transition periods between the regional rainy and dry seasons). Increases in drought frequency were also observed in the months of December and January (rainy season), particularly in the eastern region of the state, where the Cantareira reservoir system is situated. From the agro-environmental resource management viewpoint, we concluded that there is an increase in the risk of meteorological droughts in the State of São Paulo. From an academic viewpoint, this study provided further evidence supporting the hypothesis that climate change has increased drought frequency and intensity in several regions of the world.

Keywords: Standardized Precipitation Index; climate risks; nonstationary method.

RESUMO

ELEVAÇÕES NA FREQUÊNCIA DE OCORRÊNCIA DE SECAS METEOROLÓGICAS NO ESTADO DE SÃO PAULO SOB CONDIÇÕES DE MUDANÇAS CLIMÁTICAS. Elevações na frequência e intensidade da seca vem sendo observadas em diversas regiões do planeta, sendo que as mudanças climáticas são frequentemente apontadas como uma das principais responsáveis por essas alterações. Considerando os severos impactos causados por essa adversidade ambiental, o objetivo desse estudo detectar e quantificar possíveis alterações na probabilidade de ocorrência dos eventos de seca meteorológica no Estado de São Paulo. Foram utilizados dados de precipitação pluvial do projeto NASA-POWER, o qual é capaz de fornecer séries com mais de 30 anos. Os eventos de seca foram quantificados com base no Índice Padronizado de Precipitação (SPI), calculado por meio de método probabilístico não estacionário ("*the four-step algorithm*") especialmente desenvolvido para aprimorar a interpretação do SPI sob condições de mudanças climáticas. Os resultados apontaram elevações na frequência da seca meteorológica com picos máximos em meses de transição entre as estações chuvosa e seca, como março e abril.

Os meses de dezembro e janeiro (auge do período chuvoso) também apresentaram elevações na ocorrência dessa adversidade ambiental, com predomínio nas porções leste de São Paulo, incluindo o Sistema Cantareira. Sob o ponto de vista de gestão de recursos agroambientais, conclui-se que há aumento no risco climático associado à ocorrência da seca no estado de São Paulo. Sob o ponto de vista acadêmico, esse trabalho amplia o rol de evidências que suportam a hipótese de que as mudanças climáticas estejam afetando a frequência e a severidade dos déficits de precipitação em diversas partes do planeta.

Palavras-chave: Índice Padronizado de Precipitação; risco climático; método não estacionário.

1 INTRODUCTION

Drought is a natural hazard that has been observed in virtually all regions of the globe. Several studies carried out across the world (e.g. DAI 2012 and BLAIN et al. 2022) have described increases in its frequency and intensity. This statement particularly holds in the state of São Paulo, Brazil, where recurrent drought events have been observed over the last years. (PEREIRA et al. 2018). Among these episodes, the 2013-2015 water crises affected the metropolitan region of São Paulo, which is one of the most populated areas on the planet (NOBRE et al. 2016).

Among the factors leading to the changes in the probability of this hazard, the current climate change has been often regarded as the main responsible for the recurrent rainfall deficits, which are defined by observed precipitation totals considerably lower than that expected for the region and period. In this context, studies such as SENEVIRATNE et al. (2012), TRENBERTH et al. (2014), ERFRAIN et al. (2017), MARENGO et al. (2017) state that the drought events in South America may intensify over the next years due to its potential to respond drastically to excessive drying and warming. Studies based on long-term meteorological series (DUFEK & AMBRIZZI 2007) also observed significant changes in the temporal variability of the rainfall events in the state of São Paulo. In addition, PEREIRA et al. (2018) observed increasing trends in the frequency of meteorological droughts (defined by rainfall deficits), which may lead to crop failures in the state.

One noteworthy aspect of the study of PEREIRA et al. (2018) is that it applied the Standardized Precipitation Index (SPI, MCKEE et al. 1993), which is a probability-based method. The SPI has been widely used in virtually all drought monitoring systems (DMS) around the globe. The World Meteorological Organization (WMO) recommends the SPI to quantify the severity of rainfall deficits in several regions on Earth (HAYES et al. 2011). However, the study of PEREIRA et al. (2018) has two shortcomings. First, the study is based only on long rainfall records (longer than 60 years) obtained from surface weather stations. Although this strategy allowed the exclusive use of observed historical data, it led to the use of few weather stations across the state. The reason for this is the low number of long meteorological records in the state and problems related to data quality. Consequently, the study lacks spatial representation. The second shortcoming is the fact that PEREIRA et al. (2018) only detected changes in the frequency of drought events. The authors did not attempt to quantify the rate of these changes.

The first shortcoming may be overcome with remote sensing data, which has presented an increasing use in environmental studies. The accuracy of these data sources has increased over the years. In this context, the NASA POWER Project (*National Aeronautics and Space and Administration Prediction of Worldwide Energy Resource*; https://power.larc.nasa.gov/) has gained popularity as a suitable meteorological data source (BAI et al. 2010, MONTEIRO et al. 2018, DUARTE & SENTELHAS 2020). Different from other sources, it has daily rainfall data dating back to 1891. Accordingly, this project meets the 30-year period required for calculating the SPI (MCKEE et al. 1993). Moreover, NASA POWER data has shown good performance in estimating rainfall data throughout the world. AL-KILANI et al. (2021) assessed the NASA POWER's performance in Jordan. They found relatively high correlations between observed rainfall data and NASAPOWER data ($0.67 \leq R^2 \leq 0.91$). RODRIGUES & BRAGA (2021) also found high correlations between weather station data for maximum and minimum air temperature and solar radiation and their corresponding NASA POWER data in Alentejo, Portugal ($R^2 > 0.82$). With regards to the second shortcoming, the study of BLAIN et al. (2022) developed a computational algorithm that improves, in probabilistic terms, the interpretation of the SPI estimates under changing climate conditions. This algorithm, described in further detail in section 3, is based on nonstationary parametric distributions capable of detecting and quantifying the climate change effects on the probability of drought events.

In this context, and under the hypothesis that the current climate changes are affecting the frequency and severity of rainfall deficits in the state of São Paulo, the goal of this study was to detect and quantify changes in the probability of meteorological drought events in this state using rainfall data from the NASA POWER project.

2 METEOROLOGICAL DATA

The state of São Paulo (Figure 1) is situated between 26°S – 19°S and 54ºW – 46°W (crossed by the Tropic of Capricorn). It is the major industrial region of Brazil, with the highest population density and gross domestic product in the country (IBGE 2022). This state is also a major player in the agroindustry and the world-leading producer of sugarcane and citrus (CONAB 2022). Accordingly, the state of São Paulo is highly dependent on water resources. 28, 47, and 21% of this natural resource is used by agriculture, urban consumption, and

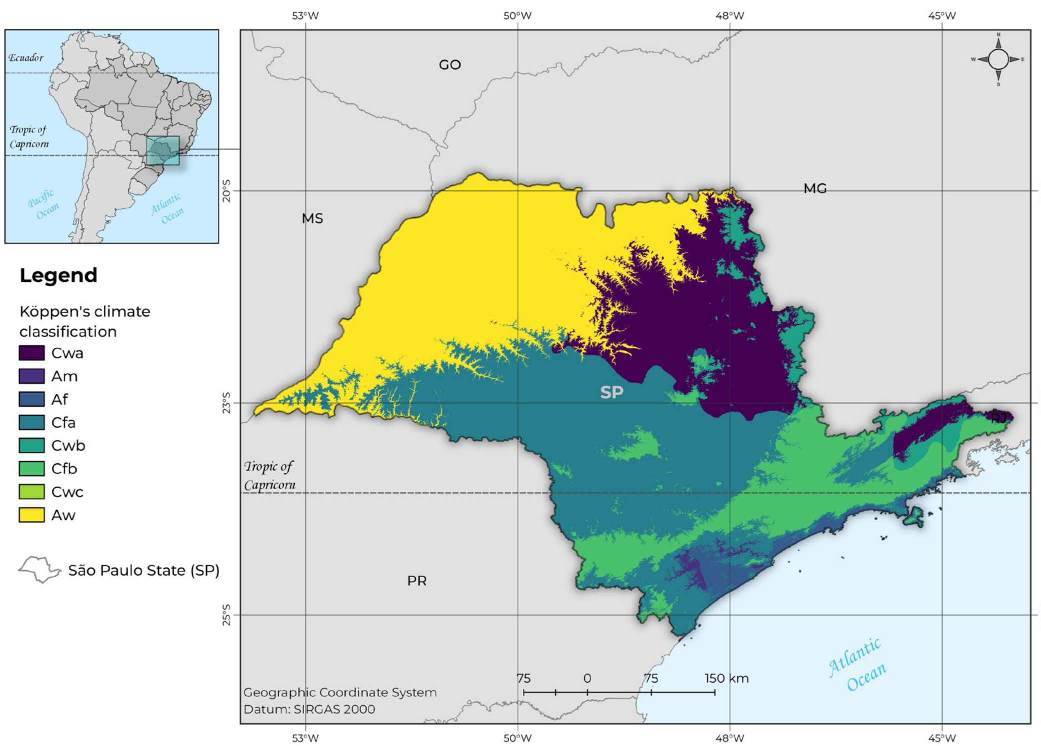

FIGURE 1 – Köppen-Geiger classification system (ALVARES et al. 2013), São Paulo, Brazil.

industry, respectively (DAEE 2020). The rainy season occurs in the Austral summer, when rainfall amounts are larger than the potential evapotranspiration totals (BLAIN et al. 2018). The rainiest months are December and January, when rainfall frequency distributions approach the Gaussian shape (BLAIN et al. 2007). As pointed out by BEN-GAI et al. (1998), this distributional shape is often observed in equatorial climates. The state also has a distinct dry season (July and August), when the rainfall frequency distributions may assume a exponential shape. The latter distributional shape is often observed in arid or semi-arid climates (BEN-GAI et al. 1998). According to the Köppen-Geiger classification system (ALVARES et al. 2013), the state has eight distinct climates conditions: Af (Tropical Rainforest); Am (Tropical Monsoon); Aw (Tropical Dry winter); Cfa (Temperate No dry season Hot summer); Cfb (Temperate No dry season Warm summer); Cwa (Temperate Dry winter Hot summer); Cwb (Temperate Dry winter Warm summer); and Cwc (Temperate Dry winter Cold summer).

This study used rainfall monthly amounts (1981-2022) from the NASA-POWER project (*National Aeronautics and Space and Administration Prediction of Worldwide Energy Resource*; https://power.larc.nasa.gov/) with a spatial resolution of 0.5º latitude and 0.625º longitude. As previously described, this databank is capable of providing meteorological series with more than 30 years of continuous records. Thus, drought indices, such as the SPI (MCKEE et al. 1993), can be obtained. The NASA-POWER is an open data source and was downloaded using the R *NASA POWER API Client v. 4.0.9* package (SPARKS 2022).

3 METHODS

The SPI is perhaps the most used drought index in the world. It is a probability-based method and the frequency distributions of its estimates are expected to have a standard normal distribution. In other words, any SPI time series is expected to have a zero mean and unit variance (HAYES et al. 1999, WU et al. 2007, BLAIN 2012). This invariability in the time-space domain is the result of a concept adopted by the SPI regarding meteorological drought, that is: a rainfall deficit occurs when the rainfall amount observed in a particular region and period is below the corresponding historical median value. In probabilistic terms, this median value corresponds to a cumulative probability of 0.5. From a climatological perspective, for both wet and dry regions/periods this median value is taken as the climatological expected value regardless its magnitude. Accordingly, when the cumulative probability of a particular rainfall amount is lower than 0.5, the SPI will assume negative values, which in turn, indicates a rainfall deficit and potentially a drought event. The lower this cumulative probability, the smaller the corresponding SPI estimate and the more extreme the drought event.

The SPI can be calculated at several time scales, which allows this index to provide relevant information for monitoring meteorological droughts (defined by rainfall amounts lower than the normal value), agricultural droughts (shortage of available water for plant growth), and hydrological droughts (associated with a deficit in the volume of the water supply). The SPI calculated at the 1- and 3-month time scales is often used to assess meteorological drought events (BLAIN & BRUNINI 2007).

Considering the above-mentioned drought definitions, the SPI calculation algorithm starts by fitting a parametric distribution to long-term rainfall series (GUTTMAN 1998). Several distributions can be used for such a purpose, however the 2-parameter gamma distribution [g(x)] – also adopted in this study – is the most common choice (MCKEE et al. 1993, HAYES et al. 1999, WU et al. 2007, STAGGE et al. 2015). This function is then used to calculate the cumulative probability of the rainfall amounts, which in turn are transformed into the standard normal distribution [N(0,1)] by a rational transformation proposed in ABRAMOWITZ & STEGUN (1965). Equations 1 to 4 describe the SPI algorithm.

$$H(x) = q+1(1-q)\ g(x) \tag{1}$$

$$q = \frac{(n_z+1)}{2(n+1)} \quad (2)$$

Where q is the probability of 0 (rain=0); n_z is the number of periods with rain=0 and n is the sample size.

H(x) is then transformed into a variable with standard normal distribution, leading to the SPI final value (equations 3 and 4).

$$SPI = -\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right), \quad (3)$$

for $0 < H(x) \leq 0.5$

$$SPI = +\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right), \quad (3.1)$$

for $0 < H(x) < 0.5$,

where:

$$t = \sqrt{\left(ln\left(\frac{1}{H(x)^2}\right)\right)}, \text{ for } 0 < H(x) \leq 0.5 \quad (4)$$

$$t = \sqrt{\left(ln\left(\frac{1}{1-H(x)^2}\right)\right)}, \text{ for } 0.5 < H(x) \leq 1 \quad (4.1)$$

$c_0 = 2.515517$; $c_1 = 0.802853$; $c_2 = 0.010328$; $d_1 = 1.432788$; $d_2 = 0.189269$; $d_3 = 0.0013$

Once the normal transformation is achieved (equations 3 and 4), the SPI estimates representing dry and wet events will present the frequency of occurrence described in table 1. These dry/wet categories were specified as a function of the cumulative probability of the rainfall amounts. At this point, it is worth mentioning that for rainfall series in which the zero value has a probability of occurrence close to or higher than 0.5, the equiprobabilistic transformation intended by the SPI algorithm may not be met (WU et al. 2007 and BLAIN 2012). In such cases, this probability-based index may fail to quantify drought events. This condition is frequently observed when the SPI is calculated at short time scales in arid or semi-arid climates or those with a distinct dry season (WU et al. 2007). Considering the climate conditions of the state of São Paulo, the SPI was calculated in this study at the 1- and 3-month time scales.

The analysis of equations 1 to 4 and table 1 indicates that the SPI was originally developed under a stationary approach in which the parameters of the parametric distribution (e.g., 2-parameter gamma) do not change over time. In other words, in its original version, this drought index assumes that the probability of rainfall deficits and surplus remain fixed over time (RUSSO et al. 2013, LI et al. 2015, RASHID & BEECHAM 2019). However, there have been observed changes in the frequency and severity of drought events in virtually all regions on the planet (STRZEPEK et al. 2010, DAI 2012, SPINONI et al. 2019). These changes violate the stationary assumption (COLES 2001, CHENG et al. 2014, ZHANG et al. 2004) and potentially modify the values of the expected frequencies presented in table 1. In this context, BLAIN et al. (2022) developed a computational algorithm based on nonstationary parametric

TABLE 1 – SPI Classification system.

SPI	*Category*	*Cumulative probability*	*Expected frequency*
SPI ≥ 2.00	Extreme Wet	0.977 – 1.000	2.3%
1.50 < SPI ≤ 2.00	Severe Wet	0.933 – 0.977	4.4%
1.00 < SPI ≤ 1.50	Moderate Wet	0.841 – 0.933	9.2%
-1.00 < SPI ≤ 1.00	Near Normal	0.159 – 0.841	68.2%
-1.50 < SPI ≤ -1.00	Moderate Dry	0.067 – 0.159	9.2%
-2.00 < SPI ≤ -1.50	Severe Dry	0.023 – 0.067	4.4%
SPI ≤ -2.00	Extreme Dry	0.000 – 0.023	2.3%

distributions (distributions with time-varying parameters). This algorithm is capable of detecting signs of climate change in SPI series, as well as quantifying their effects in the expected frequencies of the dry/wet categories shown in table 1. This algorithm has four key-steps described in figure 2. This study considerates three nonstationary models.

Model 1 (stationary):

$$H(x) = q + [1 - q]G(x, \mu, \sigma),$$

Model 2 (nonstationary; homoscedastic):

$$H(x) = q + [1 - q]G(x, \mu t, \sigma),$$

Model 3 (nonstationary):

$$H(x) = q + [1 - q]G(x, \mu t, \sigma t),$$

Where t is the time covariate.

The computational algorithm described in figure 2 selects the model that best describes the variability of the rainfall series through the ΔAICc method (Second order Akaike information criterion; BURNHAM & ANDERSON 2004). Considering the three models proposed in this study, the selection of model 1 indicates the lack of significant changes in the rainfall series. While selection of model 2 indicates significant signs of climate changes that have affected only the mean of the series, model 3 indicates that these signs have affected both mean and dispersion of the rainfall series. The ΔAICc method considered the likelihood ratio test calculated at the 5% significance level. Further information concerning this computational algorithm (Figure 2) can be found in BLAIN et al. (2022). The computational codes, developed in the R-software environment, are available at https://github.com/gabrielblain/Four-Step-Algorithm.

As previously described, the SPI was calculated at the 1- and 3-month time scales. However, as indicated by equations 3 and 4, rainfall series with a high number of rain=0 may negatively affect the performance of the SPI in assessing drought events (WU et al.

Step 1
Calculate the original SPI for the rainfall series.
Step 2
Using the standard normal distribution, calculate the cumulative probability of a SPI value of interest.
Step 3
Using the stationary gamma distribution parameters (Step 1) estimate the rainfall quantity corresponding to the cumulative probability calculated in Step 2 (Equations 3 and 4). This amount is estimated through the quantile function of the gamma distribution and a rearranged version of Equation 1 that removes the probability of zeros from the outcome of Step 2. Equations: Pr(SPI’) = [Pr(SPI-q)]/(1-q) equation 3 Pre.step3=G−1[Pr(SPI’), μ, σ] equation 4 Where Pr(.) is the cumulative probability of the variable in question, q is the probability of zero precipitation values, and μ and σ are the mean and dispersion of the distributions, respectively.
Step 4
Considering nonstationary models such as those described in this study select a suitable model (models 1, 2 or 3) for modelling the rainfall series and then calculate the time-varying probabilities of the rainfall amount estimated in Step 3. Provided that these probabilities have been estimated from the rainfall amount corresponding to the SPI of interest, it can be assumed that they are a statistical measure describing how the SPI value’s expected frequency has changed over time.

FIGURE 2 – Four-step algorithm developed by BLAIN et al. (2022).

2007) and, consequently, the performance of the computational algorithm o (BLAIN et al. 2022). Specifically, the empirical probability of zero rainfall values in dry months such as July and August in the state of São Paulo may be higher than the cumulative probabilities corresponding to severe or extreme drought categories (Table 1). In order to overcome this difficulty inherent to the nature of the rainfall frequency distributions (bounded to the left by rain=0), the computational algorithm considered changes in all SPI-1 values lower than zero. Changes in moderate and severe drought events were investigated only for the SPI-3. The latter time scale represents a 3-month moving-window that moves every month. For instance, the January SPI-3 takes into account the rainfall totals observed in November-December-January; the February SPI-3 takes into account the rainfall totals observed in December-January-February. At this time scale the empirical probability of rain=0 in the state of São Paulo is 0 or slightly higher than 0. Finally, it is worth mentioning that under stationary conditions, the extreme drought events (Table 1) have return periods equal to or larger than 43.5 years. Considering that the sample size adopted in this study is 42 years (1981-2022), we did not evaluate changes in these extreme events due to their high level of uncertainties.

The last step of this study was to plot maps of the state of São Paulo to depict the changes in the frequency and intensity of drought events as defined in Table 1. We used the R-packages ggplot2 (WICKHAM 2016); rgdal (BIVAND et al. 2021) and sf (PEBESMA 2018) for such a purpose.

4 RESULTS AND DISCUSSION

The results found in this study (Figures 3 to 5) are in line with previous studies, which described changes in the rainfall patterns of the state of São Paulo. These changes were the result of increases in the frequency and intensity of drought events (DUFEK & AMBRISSI 2007, PEREIRA et al. 2018, CORREA et al. 2022). For instance, DUFEK & AMBRISSI (2007) observed, after 1990, increasing trends in the

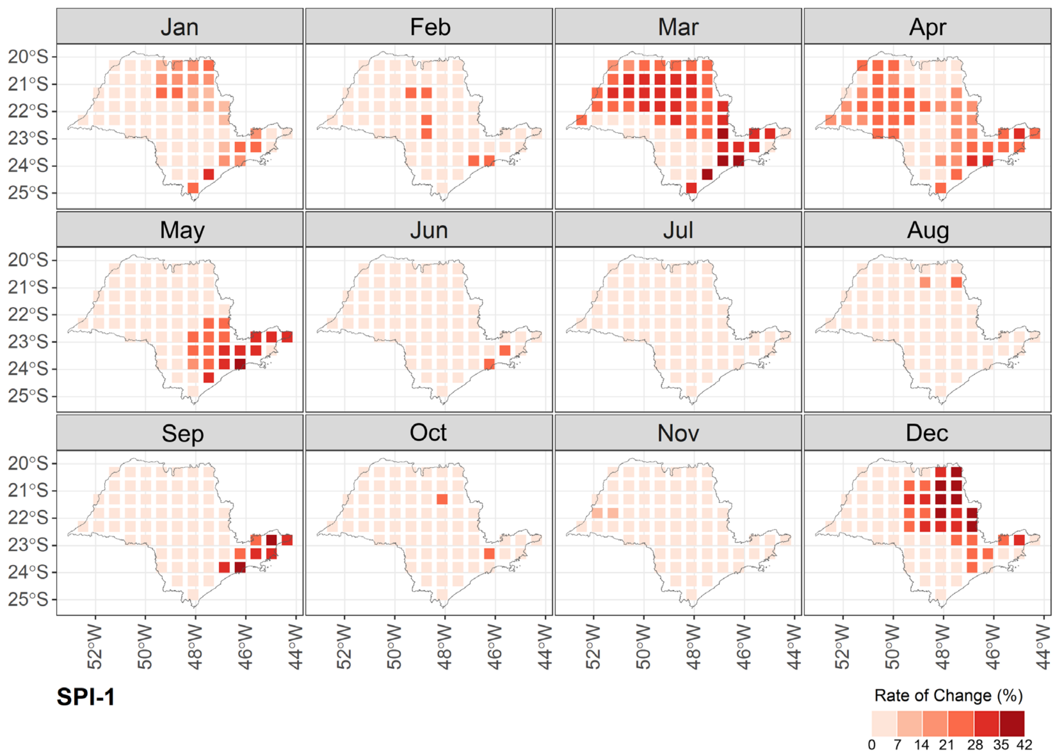

FIGURE 3 – Rate of changes in the frequency of meteorological drought events in the state of São Paulo (1-month time scale).

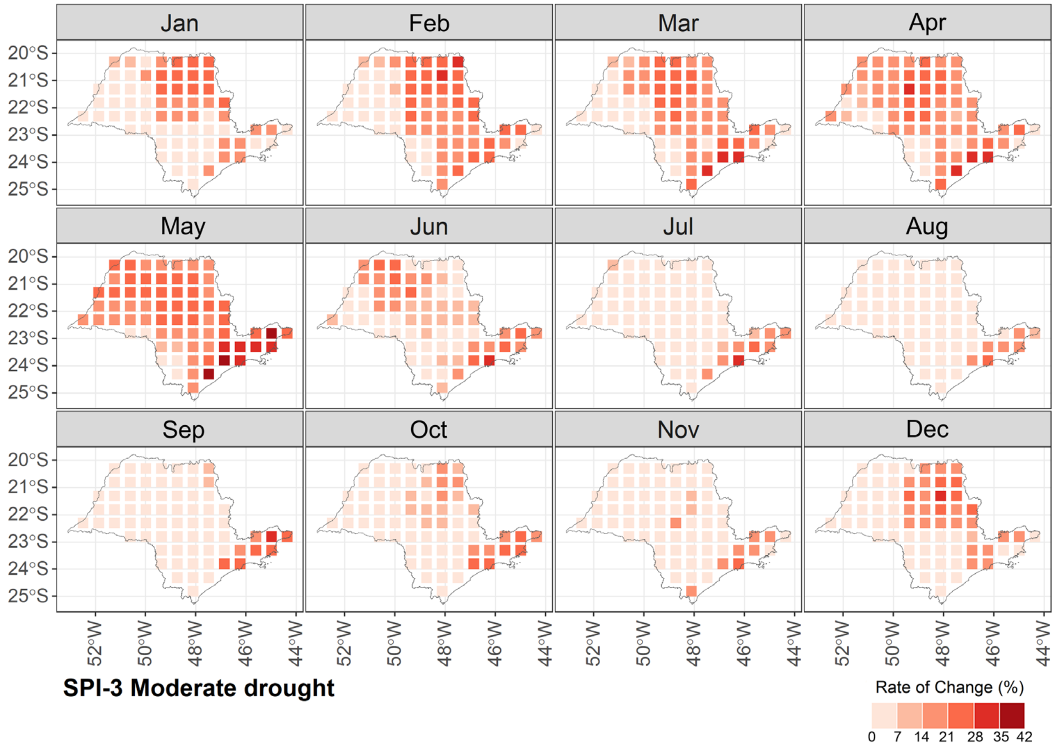

FIGURE 4 – Rate of changes in the frequency of moderate meteorological drought events in the state of São Paulo (SPI-3month).

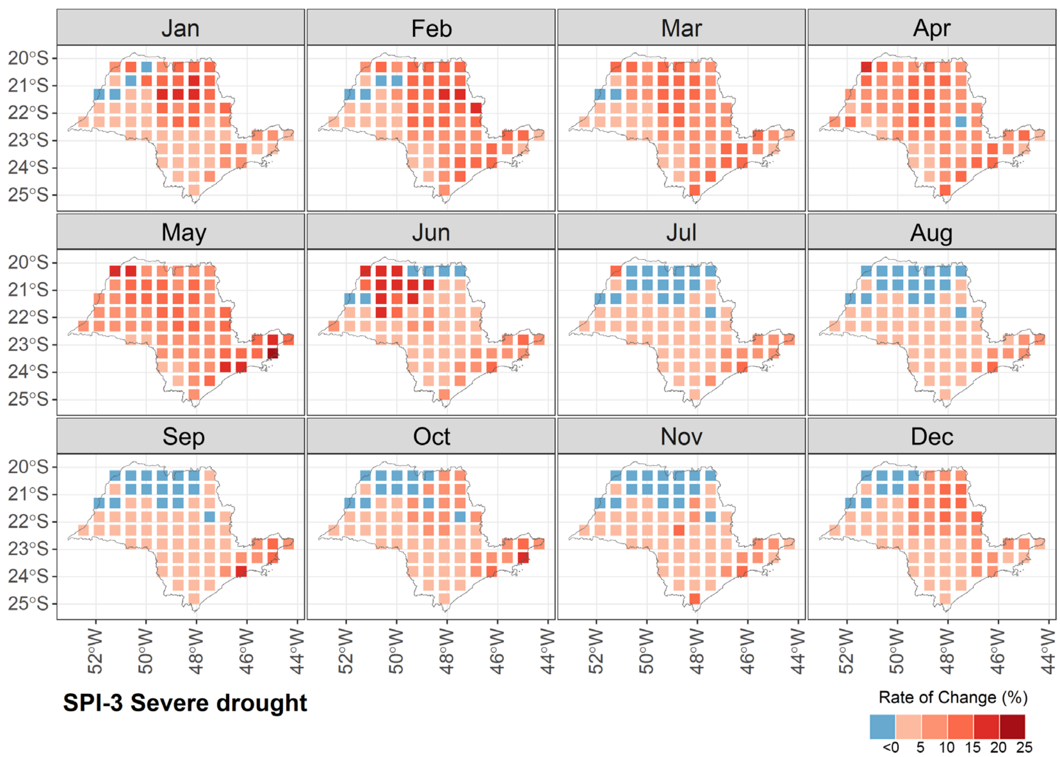

FIGURE 5 – Rate of changes in the frequency of severe meteorological drought events in the state of São Paulo (SPI-3month).

number of consecutive dry days in the state. This result is consistent with those depicted in figure 3 (SPI-1, March and April) and figures 4 and 5 for the SPI-3 of April (Feb-Mar-Apr) and, especially, May (Mar-Apr-May). Considering that these 1-month and 3-month series belong to the period between the rainy and dry seasons, we may state that the increase in the frequency of drought events depicted in figures 3 to 5 is consistent with the increase in consecutive dry days found by DUFEK & AMBRISSI (2007).

Considering the SPI-1 series, March – the last month in the rainy season – showed the highest increase in the frequency of SPI-1 values lower than 0. April and December, respectively, are the other two months with the highest increase in the probability of occurring SPI-1 values below zero. For the 3-month series, the results depicted in figures 4 and 5 also indicate significant increasing trends in the frequency of moderate and severe drought events. This statement particularly holds for the SPI-3 series between December and May.

As previously described, the significant signs of climate change found in this study are consistent with the results of previous studies, which used data from weather stations (e.g. DUFEK & AMBRISSI 2007, PEREIRA et al. 2018, CORREA et al. 2022). In addition, the results depicted in figures 3 to 5 are also in line with climate change projections derived from the regional climate model Eta nested in the global climate models HadGEM2-ES and MIROC5. Specifically, CHOU et al. (2014) applied these two models (Eta-HadGEM2-ES and Eta-MIROC5) to describe climate change scenarios in South America (2011-2040) under two Representation Concentration Pathway: RCP 4.5 (4.5 W m^{-2} radioactive force scenario) and RCP 8.5 (8.5 W m^{-2} radioactive force scenario). Among the results found by CHOU et al. (2014), we highlight the decrease in the rainfall totals projected in Southeast Brazil, which is the region where the state of São Paulo is situated. Similar results were also found by TAVARES et al. (2023). These authors assessed several water balance parameters under two climate change scenarios (warmings of 1.5 °C and 2.0 °C) and they found changes to drier conditions in several Brazilian areas, including the country's southeast region.

The changes depicted in figures 3 to 5 can also be related to departures in the atmospheric circulation patterns and decreases in rainfall amounts in the Amazon rainforest (REBOITA et al. 2015 and TAVARES et al. 2023). As pointed out by YIN et al. (2013) and JOETZJER et al. (2013), wildfires and deforestation in the Amazon rainforest lead to decreases in evapotranspiration rates and may negatively impact the rainfall patterns in central-east and southeast Brazil. Specifically for the state of São Paulo, ARMANI et al. (2022) assessed climate change scenarios (2020-2050; RCP 4.5 and RCP 8.5). These authors used the Eta model nested in four general circulation models (HadGEM2-ES, MIROC5, CanESM2 and BESM). The spatial resolution adopted by ARMANI et al. (2022) was 20 x 20 km. The results found in this later study are consistent with those of figures 3 to 5 and described a general reduction in the rainfall amounts in the state.

With regard to the hydrological impacts of drought events, this study described significant increases in the frequency of this environmental hazard in rainy months. This change is particularly relevant because it may significantly affect water reservoir recharges. In this context, we highlight the 2014-2016 water crises that negatively affected the population and the economy of the metropolitan region of São Paulo. As pointed out by (NOBRE et al. 2016), it may be regarded as the most severe drought event since 1960. Accordingly, the results found in this study, along with those of ARMANI et al. (2022), indicate the need for rational water management in the state, which has shown an increase in its water demand. This statement is particularly true for the Cantareira water system (metropolitan region of São Paulo), which has shown to be highly vulnerable to drought events (NOBRE et al. 2015).

5 CONCLUSION

Based on a nonstationary probabilistic approach, this study assessed changes in the probability of meteorological drought events in the state of São Paulo between 1981 and 2022. The results found from this analysis described significant increases in the expected frequency of rainfall deficits. These increases are particularly notable in the months of March and April when there is a transition between the rainy and dry seasons in the state. The months of December and January (rainy season) also showed increases in the frequency of this environmental hazard, mainly in the eastern area of the state (coastal region and Cantareira water system). These results are in line with previous studies based on historical meteorological series and climate change projections.

From a water management perspective, this study described significant increases in the risks associated with rainfall deficits in the state of São Paulo. From an academic viewpoint, this study provided new evidence supporting the hypothesis that climate changes affect the frequency and severity of drought events. It was also observed that nonstationary probabilistic models improve the statistical analysis of meteorological drought events. Therefore, future efforts may verify if highly complex nonlinear parametric models are capable of improving the results found in this study.

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Authors' addresses:

Letícia Lopes Martins (0000-0002-0299-3005) – Instituto Agronômico, Programa de Pós-Graduação em Gestão de Recursos Ambientais, Av. Barão de Itapura, 1481, Botafogo, CEP 13.020-902, Campinas, SP, Brasil. E-mail: leticia.l.ufv@gmail.com

Graciela da Rocha Sobierajski (0000-0002-7211-9268) – Centro de Fruticultura, Instituto Agronômico, Av. Luiz Pereira dos Santos, 1500, Corrupira, CEP 13.214-820, Jundiaí, SP, Brasil. E-mail: graciela.rocha@sp.gov.br

Gabriel Constantino Blain* (0000-0001-8832-7734) – Centro de Biossistemas Agrícolas e Pós-Colheita, Instituto Agronômico, Av. Doutor Theodureto de Almeida Camargo, 1500, Jardim Nossa Senhora Auxiliadora, CEP 13.075-630, Campinas, SP, Brasil. E-mail: gabriel.blain@sp.gov.br

* Correspondent author

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