Changes in the spatial–temporal patterns of droughts in the Brazilian Northeast

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In Northeast Brazil (NEB), severe droughts have high socioeconomic impacts. In this study, the spatial–temporal characteristics of drought were evaluated based on a new drought index at 4-km spatial resolution, derived from regional empirical relationships between a remote sensing-based index and rain-gauge-based standardized precipitation index (SPI), a well-known drought meteorological index. This index was used to compare the spatial pattern of severe drought events (1982–1983, 1992–1993, 1997–1998, and 2012–2013) of the last 30 years. Strong El Niño related droughts were found to be generally spatially limited, affecting around 30% of NEB and concentrated in the northern part of the region, while 2012 drought, which was not El Niño related, was widespread, reaching 46% of NEB. These results stressed the importance of analyzing droughts at the subregion scale using data with higher spatial resolution. Statistically significant trends ($p < 0.05$) toward drier conditions detected in the SPI time-series were linked to the tropical Atlantic Ocean warming trend, which result in an increased drought risk and social vulnerability in the region.

KEYWORDS
Brazilian Northeast, drought, drought monitoring, SPI, VHI

INTRODUCTION

Globally, the percentage area that is affected by drought has been doubled since 1970 through early 2000 (Nagarajan, 2009). There is strong evidence that those extremes are becoming more frequent, and are likely to be related to human-induced climate change (Gloor et al., 2013; Trenberth et al., 2013; Marengo and Espinoza, 2016).

In Brazil, droughts are widespread and recurrent in the Northeastern semiarid region (Northeast Brazil [NEB]), which has approximately 24 million inhabitants and a density of 24.3 inhabitants per kilometer. Since the NEB region has the highest proportion of people living in poverty in Brazil, with rainfed agriculture accounting for 95% of farmed land (IBGE, 2009), drought impacts are often severe. The combination of high spatial and temporal rainfall variability, lack of irrigation, land degradation due to inadequate soil management (Vieira et al., 2015), and the large-scale poverty in rural areas make the NEB region one of the world’s most vulnerable areas to the impacts of climate change.

In addition, rainfall network density in the NEB is insufficient to adequately monitor the high spatial variability of rainfall of the region. Therefore, traditionally rainfall-based meteorological indices used to monitor droughts (Palmer, 1965; Gibbs and Maher, 1967; McKee et al., 1993), such as the standardized precipitation index (SPI), which are estimated using rainfall station data, do not have the spatial coverage required for deriving high-resolution maps. In such areas, drought characterization using remote sensing
techniques is extremely useful because of its multi-temporal sampling and high-resolution spatial coverage. Because of this, remote sensing indices such as the vegetation health index (VHI) have been widely used as a composite remotely sensed drought index (Kogan et al., 2016). Since VHI is calculated using multiyear historical observations (anomaly relative to 30-year climatology), it can be considered conceptually similar to a rainfall-based index like SPI (Wang et al., 2014), which can only be computed when sufficiently at least 30 years of data is available. Although VHI has limitations for characterizing the severity and duration of droughts over dense vegetation canopy areas, VHI can be successfully applied in semiarid regions where water is the main limiting factor for vegetation growth (Chen et al., 2016; Kogan et al., 2016).

In this study, we developed regional relationships between the VHI remote sensing index and the drought meteorological index SPI. Based on those relationships, we developed a new drought index and multi-temporal high-resolution drought maps for the period 1982–2016 for the Northeast of Brazil, and analyzed spatial–temporal pattern and trends of drought over the region. This new index has advantages over the isolated use of VHI since it incorporates the time-variability of a key indicator of drought such as SPI, and is not constrained by the rain gauge network density because it has the spatial resolution of VHI. Because the vegetation response is not uniform across the study area, equivalent rainfall deficits will have different impacts on VHI and SPI values, which indicates that the solely use of VHI will not reflect the drought intensity as an SPI-based index.

Since climate variability in NEB is related to sea surface temperature (SST) variations, both in the Pacific and Atlantic oceans (Kayano and Capistrano, 2014; Rodrigues and McPhaden, 2014; Marengo et al., 2017a, 2017b), we compared the recent trends observed in drought maps against the time evolution of tropical SST indices.

2 | MATERIALS AND METHODS

2.1 | Data

We used monthly time series of 86 rainfall stations (Table S1 in Appendix S1, Supporting information) distributed throughout the study region and covering the period of 1982–2016 (Figure S1) to calculate the SPI for time scales of 3, 6 and 12 months (McKee et al., 1993). The stations were selected according to the data availability (time series with at least 30 years) and by their geographical location, to ensure the best possible spatial representativeness. Double mass analysis was used to investigate the consistency of rainfall dataset. Precipitation data were extracted from the Brazilian National Water Agency—ANA database available at http://www.snirh.gov.br/hidroweb/.

VHI is a remote-sensed drought index (Kogan, 1997; Kogan and Guo, 2017) calculated additively by combining two indexes: the vegetation condition index and the temperature condition index. See Text S1 for more information on these indices. VHI has been widely used in different applications, such as drought detection, assessment of drought severity and duration, drought-related losses of crop and pasture production, and early drought warning. For the purposes of this study, we used VHI at 4 km spatial and 7-day composite temporal resolution, from 1982 to 2016. The VHI data used in this study are available at ftp://ftp.star.nesdis.noaa.gov/.

Monthly SST anomalies indices were extracted from the Earth System Research Laboratory Earth (ESRL/NOAA) database. The SST indices analyzed were the “Niño 3.4 region,” the North Tropical Atlantic Index SST Anomaly (NTA) and South Tropical Atlantic Index SST Anomaly (STA). Finally, our analysis included the Atlantic Meridional Mode Index SST (AMM) obtained from ESRL/NOAA.

2.2 | Methods

Several studies in different regions have shown that VHI and SPI are correlated (Ji and Peters, 2003; Mukherjee et al., 2014; Wang et al., 2014). In this study, we performed linear regression analysis between ground-based SPI (SPIG) data against satellite-based VHI. To allow comparisons between the SPIG and VHI values, monthly VHI data were averaged within a radius of 10 km around the rainfall stations (spatial representativeness of rain gauge measurements, Burcea et al., 2012).

To take into account the time-lag effects of vegetation responses to the drought, the strengths of the linear association between VHI and SPIG were examined for 3, 6, and 12 months of accumulated rainfall, thus VHI was regressed against SPIG-3, SPIG-6, and SPIG-12. Regression for different time-lags was ranked based on the coefficient of determination ($R^2$) and the mean absolute error, and the SPI that provided the best correlation (significance level of 5%) was then selected. Once the most suitable relationships between monthly VHI and SPIG were selected, the regression coefficients (slope and intercept) from the regression analysis were spatially interpolated over the whole study area (See Text S2). Although significantly correlated with rainfall station SPIG, the index derived from the empirical relationships between VHI and SPIG should not be considered a purely meteorological index since it incorporates the effects of drought-induced senescence. Therefore, it was named here as SPI adjusted.

In the next step, VHI monthly data maps were applied to the spatially interpolated regression coefficients (Figure S2), to obtain the time series of SPI adjusted with a spatial resolution of 4 km over the entire study area for the period 1982–2016.
The derived SPI\textsubscript{adjusted} maps were then analyzed for the detection of trends using the Mann-Kendall statistics (Mann, 1945; Kendall, 1975). The Kendall tau correlation coefficient is based on the number of concordances and discordances in paired observations. In the present study, the trend analysis was calculated for each pixel value of monthly SPI\textsubscript{adjusted} with a confidence level of 95%.

3 | RESULTS

3.1 | Regression analyses

Results showed $R^2$ between satellite-based VHI and SPI\textsubscript{G} above 0.5 in 58, 70, and 44% of rainfall stations for, SPI\textsubscript{G}-3, SPI\textsubscript{G}-6, and SPI\textsubscript{G}-12, respectively, with $p < 0.05$. This result is similar to previous studies in Southwest China, which showed that the effects of droughts on the VHI signal were time-lagged from 3 to 6 months (Wang et al., 2014). Therefore, SPI\textsubscript{adjusted} was estimated from VHI based on the regression determined for SPI\textsubscript{G}-6.

3.2 | Spatial patterns of severe historical droughts

Figure 1 shows the Hovmoller diagram of monthly SPI\textsubscript{adjusted}, illustrating with different colors, the relative frequency (from monthly histograms) of the SPI\textsubscript{adjusted} for each time step over each pixel in the study area. (The maximum relative frequency for the SPI\textsubscript{adjusted} is shown in the right plot.) Visual analysis shows the major severe droughts that impacted the region, namely, 1982–1983, 1992–1993, 1997–1998, and 2012–2016.
FIGURE 2  (a) Spatial pattern of SPI_{adjusted} to 1982–1983, 1992–1993, 1997–1998 and 2012–2013 drought events. (b) Frequency histogram occurrence to the entire region study
1997–1998, 2007–2008, and 2012–2016 (gray-shaded areas of the right panel of Figure 1). Among those events, the large drought of 2012–2016, considered to be the largest drought, both in magnitude and duration, of the last three decades (Getirana, 2016; Brito et al., 2017; Marengo et al., 2017a, 2017b). The right panel of Figure 1 shows the time evolution of the peak values of relative frequency over the period of analysis, indicating a significant trend toward intensification in magnitude and duration of droughts along the period 1982–2016.

An important characteristic of the drought seen in Figure 1 is their tendency to become more expansive during strong El Niño events (e.g., 1982–1983, 1992–1993, 1997–1998).

Figure 2a shows the spatial distribution of SPI_adjusted for major drought events related to El Niño in the period 1982–2016 and the 2012–2013 drought (non-El Niño year). In terms of spatial distribution of droughts, the events of 1982–1983 and 1992–1993 show a typical El Niño pattern, with strong drought intensity in the northern part of the region (see details in Figure S3) due to the anomalous northward migration of the intertropical convergence zone—ITCZ (Uvo et al., 1998; Hastenrath, 2006). These two events affected 25% and 32% of the NEB land area (quantified by SPI < −0.5), respectively. The drought of 1997–1998, also El Niño related, shows lower SPI values to the eastern part of the study area, and mixed signals to the western area. In terms of the frequency (Figure 2b), the drought of 1997–1998 was not as severe as those of 1982–1983 and 1992–1993, affecting 20% of the NEB land area, as shown in previous studies (Kane, 1999).

The move toward more severe conditions in terms of the spatial extent of the phenomena, as indicated by the experimental frequency, is noticeable in the case of the 2012–2013 drought event, not related to El Niño. The 2012–2013 drought was characterized by a widespread impacts, reaching 46% of the NEB land area.

Pixels with negative values for SPI make up 94% of total study area during the drought event of 2012–2013. For the other three drought events, the percentage of the area under negative SPI values corresponded to 73, 85, and 82% of the study region for 1982–1983, 1992–1993, and 1997–1998, respectively. It is also highlighted that, unlike the other events, the 2012–2013 persisted for 6 years (until 2017), as also emphasized by Marengo et al. (2016).

### 3.3 Recent trends in the SPI_adjusted and its relationship to tropical SST

Figure 3 shows the spatial distributions of Kendall’s tau values for the period 1982–2016, pointing to negative SPI_adjusted trends in most of the study region indicating a statistically significant drying signal. Although positive SPI_adjusted trends are observed in several spots of the study region, the relative frequency histogram over the entirely area clearly shows predominance of negative significant trends. In a background assessment, we found that the trends toward wetter conditions observed in Figure 3 are mostly in areas that have been undergoing expansion of irrigation in recent years. For instance, the MATOPIBA area, an acronym formed by the abbreviations of the states located to the northwest of the study area within the country’s agricultural frontier, has experienced a large increase in soybean production (Salvador and de Brito, 2017). To the central of the study are, it is noticeable several areas with positive trend associated to the São Francisco River valley, where several irrigation projects were developed in recent years.

Regarding the areas with decreasing trends of SPI_adjusted, they represent about 90% of the study region and are distributed not only in the central semi-arid region, but also in the more rainy surrounding areas. It is emphasized that most areas with decreasing trends of SPI_adjusted coincide with the areas highly susceptible to desertification identified by Vieira et al. (2015). In addition, it is still important to note that the trend of land degradation in the region, combined with increased frequency of drought occurrence, may be exacerbated further by inadequate land management practices (such as slash and burning) frequently used in the region.

Figure 4 illustrates the variability of area-averaged SPI_adjusted and SST anomalies for the Atlantic and Pacific indices, namely, Niño 3.4, NTA, STA, and AMM for the period 1982–2016. Red bars indicate drier (in the case of SPI_adjusted) and warmer (in the case of SST indexes) values, while blue bars indicate wetter and colder conditions, respectively. Areas in shaded gray highlight the four
major drought events shown in Figure 2. Comparisons of the severe droughts with SST anomalies corroborate previous findings regarding the causes of the droughts, the droughts of 1982–1983, 1992–1993, and 1997–1998 are clearly associated with El Niño events, while the 2012–2016 event is associated with ITCZ northward migration followed by an El Niño event (Rodrigues and Mcphaden, 2014).

The statistical tests at the 5% significance level for the area average of monthly SPI_{adjusted} time series during 1982–2016 over the study area indicated a significant decreasing trend (Figure 4a), which suggests an increase frequency of drought occurrence in recent years. In addition, it is noted that the drought severity (negative SPI_{adjusted} areas) also increased in the last drought event.

Regarding the SST anomaly indices, no trend was found at 5% significance level for El Niño 3.4 time series in the period analyzed. The AMM, on the other hand, which describes the meridional gradient between northern and southern tropical Atlantic SST (Chiang and Vimont, 2004), showed a significant positive trend.

The role of the AMM has been well documented since the 1970s, when Hastenrath and Heller (1977) found that the interannual variability of rainfall in Brazilian Northeast is highly correlated with the position of the ITCZ. Anomalously, dry (wet) years are characterized by positive (negative) SST anomalies of around 1°C (0.5°C) north (south) of the ITCZ coincident with the decrease (increase) in trade wind strength north (south) of the equator. The trade wind decrease in the northern tropical Atlantic is the result of a northward-directed
pressure gradient force, with a low pressure anomaly centered between Bermuda and the Caribbean Islands (Hastenrath and Heller, 1977). Consequently, during the positive phase of the AMM, the precipitation over northern NEB is generally low (Rugg et al., 2016; Rodrigues and McPhaden, 2014; Hounso-Gbo et al., 2016; Foltz and Perez, 2018). In addition, regional climatic consequences are accentuated when the positive configuration of the AMM occurs concomitant with an El Niño episode (Hounso-Gbo et al., 2016).

Gloor et al. (2013) suggested that warmer than average tropical North Atlantic SSTs lock in the ITCZ more to the north than usual with the shift leading to less overall basin-wide precipitation. In a more recent study, Gloor et al. (2015) suggested that the trends observed in the tropical Atlantic have increased the frequency of extreme floods and drier than usual conditions over the Amazon basin. Our results are consistent with the conclusion of Gloor et al. (2015) in the sense that the warming in the tropical Atlantic is affecting the net water vapor transport into the continent, resulting in increased floods in the Amazon and lower rainfall in the Brazilian Northeast.

4 | SUMMARY AND DISCUSSIONS

The SPI index is recommended for drought monitoring due to its simplicity and multiscale characteristic for quantifying abnormal wetness and dryness. However, it relies upon long-term data records collected by rainfall stations which lack the spatial density required for high-resolution drought assessment. In the context of drought risk management, information such as these is relevant for subsidizing actions that mitigate drought impacts. Therefore, our study constructed high-resolution SPI adjusted time-series maps based on empirical relationships between a remote-sensing-based index and the meteorological SPI, from 1982 to 2016. This new index has advantages over the isolated use of VHI and SPI, since it includes indirectly, the key driver or threat (SPI) and an indicator of impact (VHI) through the coefficients of the regression. The performed analyses from SPI adjusted showed that this was able to identify the extreme events of drought in the region, allowing a regional analysis with a higher spatial resolution (4 km). It is also highlighted that the spatial resolution of the drought indicator is essential for impact assessment at municipal level, which is necessary to guide mitigation actions.

Considering the SPI adjusted, the results showed differences, both in space and time, among severe droughts, indicating that strong El Niño-related droughts were found to be generally spatially limited, affecting around 30% of NEB and concentrated in the northern while 2012 drought that did not have the El Niño as the driver, was widespread, reaching 46% of NEB.

Differences in oceanic and atmospheric configurations are associated to each of the events. Although the large majority of severe drought events in the region is associated with the occurrence of El Niño, this is not always the case (KANE, 1997). As shown in several previous studies, severe drought events can also be the result of a northward shift of the ITCZ. The anomalous northward migration of the ITCZ has been associated to the simultaneous occurrence of warm SST anomalies in the North tropical Atlantic and cold SST anomalies in the South tropical oceans (Hastenrath and Heller, 1977; Hounso-Gbo et al., 2016). The beginning of this drought event (2011–2012) was associated with negative SST anomalies in the central Pacific (La Niña) concomitant with positive SST anomalies in the tropical North Atlantic, which favored a northward migration of the ITCZ (Rodrigues and McPhaden, 2014). During 2015–2016, on the other hand, a strong El Niño event increased and prolonged the effect of the drought (Marengo et al., 2017a, 2017b). Previous studies have considered the 2012–2016 drought, the most severe of the last 30 years, both in duration and intensity (Paredes-Trejo and Barbosa, 2017; Marengo et al., 2017a, 2017b).

Statistically significant trends toward drier conditions detected by the SPI adjusted index suggest that the severe drought which affected the region in recent years could be related to warming trends observed in the tropical Atlantic ocean. However, further analysis is required to verify this. Furthermore, the combination of increased land degradation (Tomasella et al., 2018) and higher frequency of severe droughts are likely to make the region more vulnerable to drought in the near future. These results are in agreement with the projected intensification of drought in the region under climate change (Marengo et al., 2017a) and demonstrate the increasing need for drought mitigation in NEB.

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SUPPORTING INFORMATION
Additional supporting information may be found online in the Supporting Information section at the end of the article.

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